Examining the human factors that influence the adoption of self-service business intelligence within the banking sector of South Africa

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II Acknowledgement

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III List of Common Acronyms

Acronym	Meaning
BI	Business Intelligence
SSBI	Self Service Business Intelligence
IT	Information Technology
PC	Personal Computer
TAM	Technology Acceptance Model
DOI	Diffusion on Innovation
TOE	Technology-Organisation-Environment
UTAUT	Unified Theory of Acceptance and Use of Technology
TPB	Theory of Planned Behaviour
MPCU	Model of PC utilisation
ETL	Extract, Transform and Load process
KMO	Kaier-Meyer-Olkin results
JF	Job Fit
CP	Complexity
ATU	Affect Towards Use
LTC	Long Term Consequences
SF	Social Factors
FC	Facilitating Conditions
AD	Adoption of SSBI

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VI Abstract

By making use of Business Intelligence (BI), the business is able to extract relevant information that can be used within their decision-making processes. However, due to the challenges faced within the traditional form of BI, such as limited human capital, complex processes and tools, the ability to provide effective and efficient information to the business is hindered. According to Considine & Cormican, (2016), simply adopting self-service technologies into the current business processes, allows the business to observe benefits such as cost savings and an increase in customer satisfaction. Self-Service Business Intelligence (SSBI) is one of these solutions, that has been shown to provide business users with the opportunity to become self-reliant in making business-critical decisions within the need of a BI specialist. The aim of this research has been to examine the human factors which play a role in the adoption SSBI within the banking sector of South Africa. During the literature review, it was deemed that the Model of PC Utilisation (MPCU) framework was the best fit to examine the human factors that influence the adoption of SSBI and testable hypotheses were formulated based on its constructs. The research employed a quantitative approach via the use of an online survey through Google Forms to collect responses from a specific group of employees within the "Big Four" banks of South Africa. A total of 257 usable responses were received and using IBM SPSS Statistics v28, statistical analyses were conducted in order to determine the significance of the hypotheses. The regression analysis revealed that the MPCU framework could explain 69.2% of the phenomena of SSBI adoption, indicating that the human aspect plays a significant role in the adoption of SSBI within the banking sector of South Africa. Two of the model constructs namely, Job Fit and Complexity were found not to be significant predictors of the adoption of SSBI while Affect Towards Use, Long-Term Consequences, Social Factors and Facilitating Conditions all predicted the adoption of SSBI. The results indicated that the participants were more concerned with the availability of the SSBI models and data while being heavily influenced by management or social factors to adopt and integrate into the SSBI methodology. The study contributes to academia by providing evidence that human factors are significant contributors to the adoption of SSBI while also affirming that the users highly consider the formatting of the reporting dashboards during their adoption. It is believed that these findings should be considered by the industry while developing and implementing SSBI solutions within their businesses.

Keywords: Business Intelligence, Self-Service Business Intelligence, Banking, Adoption, Model of PC Utilisation (MPCU)

Chapter 1: Introduction and Research Background

1.1 Introduction

According to Aničić et al., (2020), costs and the management of the costs are a great factor that influences an enterprise substantially. In order for a business to report higher profits, it would need to constantly evolve, and increase its revenue, while expanding its overall customer base (Owusu, 2017). In recent years, data has exponentially grown in value to a business and can be considered one of the greatest assets to an enterprise in order for it to achieve the goal of higher profits (Hartl et al., 2016). To improve the efficiencies within a business, businesses must proactively seek out alternative and innovative opportunities as well as technologies that aid in providing a competitive advantage within the market (Ain et al., 2019; Caseiro & Coelho, 2019; Immhoff & White, 2011; Sulaiman & Gómez, 2018). This sentiment is echoed by Considine & Cormican (2016), who stated that by making use of various self-service technologies, businesses are able to reap the benefits of cost savings and customer satisfaction. Financial institutions are no different. According to Owusu et al., (2017), the rapid changes within the banking industry brought on by globalisation, competition and strategy development is forcing the industry to make use of the data available to them in a simple and faster manner. Core areas within the banking industry such as sales and marketing are substantially driven by the data records that are generated and gathered relating to the clients. This is the core responsibility of the Business Intelligence (BI) department, which combines tools, data and processes in order to produce meaningful business information that can be used within the decision-making process (Lautenbach et al., 2017). A key requirement within a financial institution is the ability to make decisions timelessly. This has been achieved by embracing the use of the data available to them, the financial institutions are able to observe trends and opportunities within the market to ensure that they have a competitive advantage (Hartl et al., 2016). According to (Ali Khan et al., 2010), another important aspect of data within the bank which needs to be coupled with speed and accuracy, refers to the detection of fraud. This can only be achieved if the decision-makers can timelessly view the information relating to the client and the potential fraudulent transaction(s). These observations only further illustrate the need and importance of the information produced within the BI departments of the financial institutions as it has a clear impact on the profits of the institution.

Traditionally, BI was required to provide insights into the business by consolidating and analysing the available data that can then be used within the decision-making process (Aljarba et al., 2019; Considine & Cormican, 2016; Jooste et al., 2018; Lautenbach et al., 2017; Muntean, 2018; Olexová, 2014). The size of the BI departments and their limited availability of human capital pose a large risk to the business in not being able to obtain relevant information at the appropriate times (Aljarba et al., 2019; Stjepić et al., 2021). BI departments are faced with considerable peril in the ability to produce information due to limited human capital and the constant changes and challenges relating to their tools, processes, and reporting methods (Aljarba et al., 2019; Olszak, 2016; Owusu, 2017; Stjepić et al., 2021).

In recent years, BI has seen a significant shift towards a more dynamic self-service approach, commonly referred to as Self-Service Business Intelligence (SSBI) (Maryska & Doucek, 2017). SSBI provides an opportunity for all decision-makers within the business to become self-reliant during the decision-making process. The SSBI methodology encourages the users to extract the information from the various data models and tool without the need of a BI specialist,

therefore, freeing up the BI resources and allowing the specialists to focus on their primary task of creating business relevant data models that assist in the decision-making process (Alpar & Schulz, 2016; Lennerholt et al., 2018; Lennerholt & van Laere, 2019).

Although the adoption of BI and SSBI is not a new concept and has been researched by many different authors (Ain et al., 2019; Considine & Cormican, 2016; Hatta et al., 2015; Olexová, 2014; Puklavec et al., 2018), the main focus of the research has been on an organisational level and how the software is perceived by the user (de Waal & Budree, 2022; Hatta et al., 2015; Oliveira & Martins, 2011). It has been observed that limited research has been conducted on the adoption of SSBI from a human factor aspect and how these factors affect the adoption of SSBI (Jooste et al., 2018; Weiler et al., 2019). Therefore, for these reasons, the aim of this research is to examine the human factors which play a role in the adoption of SSBI within the banking sector of South Africa.

1.2 Problem Statement

Various research papers that have been published over the years relating to the adoption of BI covers the topic mainly from two aspects namely, from the organisational implementational point of view and additionally from how the technology is received by the users (Ain et al., 2019; Considine & Cormican, 2016; Hatta et al., 2015; Olexová, 2014; Oliveira & Martins, 2011; Puklavec et al., 2018). A significant gap in research which has been observed relates to how the adoption of SSBI has been studied from an individual's point of view. The main oversight has been how human factors such as skill levels, attitudes, and authority levels affect the business decision-makers adoption of SSBI (Jooste et al., 2018; Weiler et al., 2019). An enterprise can implement the best systems and have the most detailed policies regarding the incorporation of SSBI within the enterprise but if we do not understand the driving factors around the employee's (i.e. the human aspect) then all of that is for nothing. A call to investigate this aspect of the adoption was made during the research conducted by Weiler et al., (2019).

This research aims to add to the current body of knowledge relating to the adoption of BI and SSBI. The research will make use of a relevant framework in order to examine whether the various human factors play any part in the adoption of SSBI within the banking sector of South Africa.

1.3 Purpose of the Research

Given the challenges mentioned in the above sections, the purpose of this research is to fundamentally examine whether the various human factors associated with an individual play a significate role in the overall adoption of the SSBI reporting methodology within the banking sector of South Africa.

1.4 Research Questions

To achieve the purpose of this research, the following research question has been formulated.

RQ_1: What influence does an individual's human factors have on their adoption of SSBI within the South African Banking Industry?

1.4.1 Research Sub-Questions

By making use of sub-questions, we can develop a deeper understanding of the research paradigm while exploring further the research question. Together with the research question, the sub-questions aim to provide context to the conclusion and subsequent suggestions of the research.

SQ_1: What impact does the influence of a manager, colleague or business have on the adoption of SSBI?

SQ_2: What effect does the structure of the SSBI reporting models have on an individual's adoption of SSBI?

SQ_3: How does an individual's job requirement(s) influence their adoption of SSBI?

1.5 Research Objective

In conjunction with the research questions proposed above. The following objectives have been identified for this research:

Main research objective:

RO_1: To explore the effect that human factors have on the adoption of SSBI through the use of a relevant adoption framework.

Sub research objective:

RO_1: To identify the impact that an individual's job requirements have on the adoption of SSBI.

RO_2: To evaluate the effect that social influences have on the adoption of SSBI.

1.6 Assumptions

In this research, it has been assumed that the respondents to the online survey have done so ethically, and without any malicious intentions. Further assumptions are that each respondent has given objective responses based on their own experiences and with the goal of the research in mind.

1.7 Significance of the Research

The results of the research are beneficial to the various organisations (particularly within the financial sector of South Africa) that are interested in the successful implementation of SSBI. This is due to the alternative considerations relating to the adoption of SSBI, focusing more on the humanistic aspect instead of an organisational angle. BI departments including their executives and analyst can make use of the research findings to plan the development of their SSBI reporting dashboards to ensure that their functionalities and designs cater for the requirements best suited to the adoption of SSBI. The research will also add to the current body of knowledge that identifies and discuss the human factors that drive the adoption of technology.

1.8 Structure of the Dissertation

The structure of the research will follow the following path:

Chapter One: indicates the introduction section of the research. This section discusses the research problem identified; it will highlight the gap in the literature that the research is attempting to cover as well as provide a high-level overview of the process to be followed within the research.

Chapter Two: is the literature review. In this chapter, peer review research will be reviewed relating to the topic of adoption and SSBI. This information will be used to examine the research problem while producing the testable hypothesis that can be used to answer the research questions posed in section 1.4

Chapter Three: relates to the research design and methodology. This chapter highlights the choices made regarding the design of the research as well as the approach that will be followed while collecting and analysing the data.

Chapter Four: refers to the analysis section of the research. In this section, the results of the online survey will be tested and presented in a variety of different formats. These results will later be used within the discussion chapter of the research to analyse the research question(s).

Chapter Five: is where the finding of the research is discussed in relation to past research. A conclusion to the research questions was drawn, while appropriate recommendations were made for future research opportunities.

Chapter 2: Literature Review

2.1 Introduction

Within this literature review chapter, the researcher aims to provide a foundational background of the BI and the SSBI reporting methodologies by exploring and evaluating them against previously published research. The review made use of Google Scholar as its predominant source of articles. According to Jacsó, (2005), the reason one would make use of Google Scholar is due to the large repository of databases to which it has access. A systematic literature review (SLR) was conducted in which relevant articles relating to keywords such as "Business Intelligence", "Self-Service", "Adoption", "Adoption Framework" and "MPCU framework" were explored and examined. The remaining sections of Chapter 2 is the result of the conducted SLR.

2.2 Background

Over the years, the importance of data to a business has grown considerably and is considered as an extremely valuable asset to a business overall (Gangadharan & Swami, 2004; Hartl et al., 2016). Businesses are constantly in competition with one another to grow their customer bases, increase sales, and ultimately report higher profits (Owusu, 2017). In order for financial institutions to operate with efficiency, they need to observe business trends, while identifying potential opportunities as well as challenges based on the data at hand which is the core objective of business intelligence (BI) (Lautenbach et al., 2017). Due to this agenda and the fact that the environments are in a constant state of change, businesses need to make use of the various dynamic technologies available, which will assist them in gaining a competitive advantage while gathering valuable data/information that can be used to improve their core services (Ain et al., 2019; Caseiro & Coelho, 2019).

The core goal of a BI department is to provide insights by consolidating and analysing the available data which can be used within the decision-making processes of the business (Aljarba et al., 2019; Considine & Cormican, 2016; Jooste et al., 2018; Lautenbach et al., 2017; Muntean, 2018; Olexová, 2014). The BI field is under constant change, therefore requiring continuous research due to the addition of new tools, processes, and methods in order to deal with the immense need for data and knowledge (Olszak, 2016; Owusu, 2017). Constant changes, the size of the BI departments and their limited human capital together pose a number of risks to a business and need to be considered in order to ensure that information can be freely provided and consumed within the business (Aljarba et al., 2019; Stjepić et al., 2021). The business needs to proactively look for innovative approaches which can be used to give them a competitive advantage within the market (Immhoff & White, 2011; Sulaiman & Gómez, 2018). BI has seen a significant shift in recent years, with the introduction of the dynamic self-service business intelligence (SSBI) reporting methodology (Maryska & Doucek, 2017). Understanding the adoption of BI is not a new concept and there have been a number of papers published on the matter (Ain et al., 2019; Considine & Cormican, 2016; Hatta et al., 2015; Olexová, 2014; Puklavec et al., 2018). The adoption of BI and SSBI has over the years been examined from two aspects namely; the organisational implementation point of view and how the technology is received and perceived by individuals within the business (Hatta et al., 2015; Oliveira & Martins, 2011). There has been limited research on the adoption of SSBI from a human aspect and the various factors that drive the adoption (Jooste et al., 2018; Weiler et al., 2019).

This literature review will be looking at BI and how it has evolved over the years into a dynamic SSBI model. It will further investigate the significant human factors which play a role in the subsequent adoption of SSBI by making use of an appropriate adoption framework in order to create testable hypotheses that can be used to answer the research question posted in Chapter 1.4 above.

2.3 Business Intelligence

2.3.1 Background

The term Business intelligence has been used for many decades and was initially posed as a description of a system which produced information that was consumed within the decision-making processes of a business (Eggert & Alberts, 2020; Liang & Liu, 2018). According to Chen et al. (2012), BI has transitioned through three significant phases over the years. These phases have been summarised based on the time periods, their core driving forces, and the subsequent enhancements to the BI field within Table 1 below.

Shift	Period	Summary of period
Phase 1	1970s	• Focus was given to the businesses in house transaction systems. • Data was extracted, transformed and loaded (ETL) into relational database management systems (RDBMS) to ensure a structured format was achieved for the data analysis. • Statistical methods were prominently used for the analysis of the data.
Phase 2	2000s	• Web-analytics and the information collected by the Web 2.0 applications is considered to be the driving force of the second phase of BI. • Data was collected and stored in its unstructured "raw" form and was produced externally to the business. • Analysis capabilities such as web and text mining were incorporated into the traditional analysis methods.
Phase 3	2011-	• With mobile technology usage surpassing the traditional forms of PCs, focus shifted to the collection and analysis of unstructured mobile and sensor data sources. • Data analysis focused on the person, their location(s) and contents consumed.

Table 1: The shift in BI

Although BI has continued to evolve with each phase it has been faced with, its primary goal has remained rooted in the analysis of the data, based on a number of articles BI aims to consolidate and analyse the available data from the various internal and external data sources in order to drive managerial decisions, improve on the current business processes, while also reducing the costs faced by the business (Aljarba et al., 2019; Considine & Cormican, 2016; Jooste et al., 2018; Lautenbach et al., 2017; Muntean, 2018; Olexová, 2014). Caseiro and Coelho (2019) highlights that although these goals generally benefit the managerial aspect of a business, it too has an important role to play in the operational processes of a business and how information is generated and shared amongst the various actors and stakeholders of the business.

2.3.2 Definition

There is no singular definition for BI within the literature however, there are a number of commonly agreed-upon constructs which are encompassed in the majority of the definitions (Caseiro & Coelho, 2019; Hatta et al., 2015). Various definitions from the literature have been synthesised within Table 2 below, allowing us to highlight and identify the common themes and concepts within each definition.

Definition	Key Concepts	Author(s)
A process of gathering internal and external data sources which are meaningful to the business and are used within decision making.	• Data collection • Knowledge generation	(Hartl et al., 2016)
A number of processes and applications which gather, store, and analyse data to be used for better decisions.	• Data collection • Data storage • Knowledge generation	(Olexová, 2014)
The use of a technology system which assists in the decision-making process of the organisation.	• Technology driven • Knowledge generation	(Vosloo & Naidoo, 2019)
The use of an analytical tool(s) to gather, store and produce knowledge which is to be used by the decision makers of the business.	• Data collection • Data storage • Knowledge generation	(Hatta et al., 2015)
The generation of information and knowledge used within the decision-making process by processing data through information systems.	• Data processing • Knowledge generation	(Hawking & Sellitto, 2015)

Table 2: BI Definitions

Based on the summarised information presented in Table 2, we are able to observe that data collection, storage and the generation of knowledge are common themes throughout the various BI definitions presented in the literature. Even though there are slight differences in the wording of each definition, they are all at a core fundamentally the same. Illustrating the importance of BI within the growth and decision-making of a business.

2.4 Importance of Business Intelligence

As the numerous definitions for BI imply, the creation of knowledge is of utmost importance within the BI field. BI allows the business to consume large amounts of data from both internal and external sources (Hartl et al., 2016), which can be in a structured or unstructured format (Ain et al., 2019; Hartl et al., 2016). The gathered data can then be transformed and can be made accessible to various users within the business in a format which can be understood by the business users. By creating a well-structured, single source of information for the business, BI is facilitating the generation of business knowledge. Through the use of data mining and analytical techniques, various types of performance and operational reports can be generated. This allows a business to produce forecasts which can assist in the making of educated business decisions from both a business strategy and operational viewpoint. This can reduce business expenses while improving processes and efficiencies, ultimately benefiting the business's profit line (Linden, 2021; Owusu, 2017; Prakash Verma & Sharma, 2021; Wiradarma et al., 2017).

The suggested benefits brought on by BI from a variety of literature have been briefly summarised as follows; i) ensuring that the business stays relevant within the market, ii) identifying and making adjustments to the business processes to increase the efficiency/performance of the business, iii) assisting and improving in the decision-making process, iv) identify potential issues faced by the business, v) formulate new business opportunities (Ain et al., 2019; Caseiro & Coelho, 2019; Jalil et al., 2019; Jooste et al., 2018; Owusu, 2017; Wiradarma et al., 2017).

2.5 The Business Intelligence elements

BI encapsulates numerous elements in order to achieve its goal of collecting, storing, manipulating, and presenting information to the business (Johannessen & Fuglseth, 2016). Each of these functional elements will be briefly discussed below.

2.5.1 Technology

The technology element encompasses a variety of systems and technology which together cater for the requirements of BI. Two broad groups can be identified as i) Back-end systems which include the hardware such as the storage capacity and the data warehousing software in which the data from various sources (structured or unstructured) is collected and stored for processing purposes at a later stage and ii) Front-end systems that are used to present the information to the business users (Eggert & Alberts, 2020; Michalczyk et al., 2020; Olexová, 2014).

2.5.2 Data

Raw data has with time, seen a shift in its importance within the business options (Hartl et al., 2016). This data is transformed into valuable business information that can be used to observe the business's current performance through the use of rendered reporting dashboards. It also plays an important role in predictions and analyses ultimately used within the decision-making processes of the business (Caseiro & Coelho, 2019; Michalczyk et al., 2020).

2.5.3 Applications

A range of applications are used within the BI processes. There are applications that are primarily used by BI analysts in order to manipulate and generated data into consumable formats such as Microsoft SQL, while others are used by the end users (Olexová, 2014). These frontend systems such as Microsoft Excel, Tableau and, Qlikview are used by BI analysts to render the data into consumable dashboards which assist the business end users in making business-critical decisions timelessly (Michalczyk et al., 2020).

2.5.4 Processes

The BI processes can be viewed as all the processes and procedures which are used to create the information consumed within the business (Caseiro & Coelho, 2019). Processes such as the ETL process is the backbone of BI and allows the data to be absorbed into the warehouse and consumed by the various applications and users within the business (Eggert & Alberts, 2020; Michalczyk et al., 2020)

2.5.5 People

There are several types of users which are involved throughout the overall BI process. These users can be grouped into the following categories: i) casual users, referring to the general consumers of the information that is generated by the BI analysts, ii) power users, refers to the BI analysts or users that are able to manipulate and create meaningful information from the underlying raw data, and finally iii) the IT users, which are the database administrators that manage the backend systems, processes, technology, and applications which are used throughout the entire BI processes by all its users (Lennerholt et al., 2018; Michalczyk et al., 2020).

2.6 Challenges faced in Business Intelligence

Ensuring that the business is able to make decisions timelessly is a key challenge faced by many BI departments, however, each of the elements discussed earlier has its own unique challenges which affect its performance within the BI process (Richards et al., 2019). These changes will be briefly discussed below.

2.6.1 Technology

The technology aspect is still one of the greatest challenges currently faced in BI (Sulaiman & Gómez, 2018). Not having a strong foundation in place will cause fractures in a builder and this is no different for the BI department. Having the correct back-end systems in place such as the correct hardware and sufficient storage space for the initial data sources as well as any data source created within the BI department is pinnacle in ensuring that there are no ripple effects throughout the remaining BI elements (Michalczyk et al., 2020; Olexová, 2014).

2.6.2 Application

Selecting a reporting tool which will be utilised within the business relies heavily on the current system architecture in place and whether the reporting tool can be integrated into the architecture while allowing room for further future growth (Aljarba et al., 2019). BI reporting models cannot be produced without a clear understanding of the business, its strategy, and the user's requirements from the report(s). Each frontend BI system should be designed for a variety of different users while catering for the variety of skill levels which each user possesses (Linden, 2021; Michalczyk et al., 2020; Popovič, 2017)

2.6.3 Processes

Ensuring that the data is available for the business relies heavily on the various ETL processes which have been put into place. The complexity of each of these processes has increased due to the introduction of external data sources and the data quality issues which these sources bring about (Alpar & Schulz, 2016; Michalczyk et al., 2020). Unforeseen technical issues impacting the ETL processes can also have drastic implications on not only having the data ready for consumption within the BI processes but also in the final reports used within the decision-making process by the business (Michalczyk et al., 2020).

2.6.4 Data

Data has a number of challenges which could hinder the effect of BI within a business. These changes relate to the collection of data which has seen a shift from internal only to both internal and external data sources (Hartl et al., 2016). With the addition of external data sources being consumed, the structure and quality of data may be questionable at times and processes need to be put in place to ensure that the data can be consumed with a degree of confidence within a business (Aljarba et al., 2019; Michalczyk et al., 2020). Linden, (2021) explains that data access and access control are key challenges faced within the BI department, this is to ensure that only the users which require access to the data are able to view and work with the data.

2.6.5 People

Support, training, and lack of system knowledge is shown to be the casual users' biggest downfall in BI (Gudfinnsson & Strand, 2017), while power user, on the other hand, can be inundated with ad-hoc reporting requests causing bottlenecks in the report development and information delivery processes to the business (Lennerholt et al., 2018). The challenges faced by IT users relate majority of the time constraints required to ensure that the systems are up and running efficiently, ensuring that the end users are able to consume the data as and when it is required within the decision-making process (Michalczyk et al., 2020).

2.7 Self-Service Business Intelligence

2.7.1 Background

As the amount of data captured and stored in the current day and age has grown and with the increased demand for data presentation and analytical reporting over recent years, a requirement for a flexible user-friendly approach to BI has emerged (Lennerholt & van Laere, 2019; Maryska & Doucek, 2017; Weiler et al., 2019). Self Service Business intelligence (SSBI) is the latest phase within the BI field, which can be viewed as the logical next step in an ever-changing environment (Bhat, 2020; Olszak, 2016; Owusu, 2017; Sulaiman & Gómez, 2018). The core essence of SSBI has the same methodologies and processes as the traditional BI approach (Aljarba et al., 2019), it, however, caters for an additional dynamic aspect in which the end users (usually managerial but in some cases operational staff) are able to access, manipulate, and extract business-critical information themselves without the assistance of a BI specialist (Lennerholt et al., 2018; Michalczyk et al., 2020; Schuff et al., 2018; Weiler et al., 2019).

This ideology will, in turn, alleviate the pressures faced by the BI departments to create and present reports to the business, allowing them to focus on ensuring that the most updated and relevant information is available in the various reporting models that can easily be consumed by the business in order to drive the decision-making process (Aljarba et al., 2019; Passlick et al., 2017; Weiler et al., 2019). This goal can be achieved with the use of additional software that provides the casual information consumer with various abilities such as importing, manipulating, and extracting critical information in an intuitive manner that does not rely on additional resources and business area as and when the business requires this information (Bhat, 2020; Johannessen & Fuglseth, 2016).

2.7.2 Definition

SSBI should not be seen as something different from the traditional form of BI but merely as an "addition tool in the tool-shed" which can be used to achieve the general BI goals of making information available for an easier decision-making process (Aljarba et al., 2019; Weiler et al., 2019). A commonly agreed upon definition for SSBI is as follows: The additional tools implemented within the BI environment that allows the consumers of BI to become independent of the BI departments in order to obtain business information for decision-making (Bani-Hani et al., 2018; Immhoff & White, 2011).

2.7.3 Different Types of Self-Service Business Intelligence users

SSBI is grouped into three different user categories, namely; Casual, Power and IT user, each of these categories have their own definition and requirements within the process which will be briefly discussed below (Alpar & Schulz, 2016; Michalczyk et al., 2020).

2.7.3.1 Casual user

The casual users are generally the consumers of data that have minimal analytics knowledge. These users are usually granted access to the reporting models and dashboards within the business while only having the ability/expectation to manipulate and consume the information as presented within the reporting model. These are for example business end users, managerial, and operational staff (Michalczyk et al., 2020).

2.7.3.2 Power user

A power user has slightly more access than the casual user and has the ability to create the information which is viewed within the business. They are typically required to make sure that the data is representable within the reporting models to the business in a format which is easily understood and consumable. The power user category usually covers the BI Analysts and data scientists (Alpar & Schulz, 2016; Michalczyk et al., 2020).

2.7.3.3 IT user

The IT user forms part of a group of users such as database administrators (DBA), developers, and data architects, who are responsible for ensuring that the data from the various internal and external data sources are in place. These users would create the ETL processes to ensure that the data is available while also managing the state and access to the various databases that are being consumed within the organisation by the Power and casual users (Alpar & Schulz, 2016; Immhoff & White, 2011; Michalczyk et al., 2020).

2.8 Benefits of Self-Service Business Intelligence

The benefits of SSBI have been well documented within the literature (Lennerholt et al., 2018; Lennerholt & van Laere, 2019). The first and foremost benefit that should be mentioned is the flexibility that SSBI achieves by allowing the various users (both power and end users) access to the data, which in part enables these users to be more self-reliant within the decision-making process. This will improve the time needed to make business-critical decisions

as the end-users do not need to wait for a third party to extract the information that they require (Lennerholt et al., 2018; Lennerholt & van Laere, 2019).

An added benefit of providing self-reliance through SSBI is that the BI staff (IT and Power users) are free to focus on their primary responsibilities, such as ensuring that the data is available and accurate for the reporting processes (IT users) and producing business-critical information that is formatted and presented within the reporting models in such a way that the business end-users are able to perform the analytics/data extracts themselves (Power users) (Alpar & Schulz, 2016; Immhoff & White, 2011; Schuff et al., 2018). Cost saving is evident when an SSBI methodology has been adopted. The cost savings are a multifaceted measurement, partly due to the improved efficiencies in the decision-making process that are achieved by providing the business users with the ability to identify the information they required with easy. Freeing up the time spent on ad-hoc request by the BI staff allows for more focus to be given to information and knowledge generation through the use of the self-service reporting models created for the business. Lastly, customer satisfaction will also improve due to the efficiencies implemented within the decision-making processes via the use of SSBI (Considine & Cormican, 2016; Daradkeh & Al-Dwairi, 2017; Lennerholt et al., 2018).

2.9 Challenges faced by Self-Service Business Intelligence

As with the challenges identified in BI above in section 2.6, SSBI has brought on its own additional challenges to each of these elements. These additional challenges will be briefly discussed below.

2.9.1 Technology

While web-based interfaces have gained popularity in recent times to handle the demand and complexity of the SSBI model, it has also sparked additional security challenges that need to be addressed in order to ensure that only relevant users are able to access these sites as well as consume the data presented within the site (Aljarba et al., 2019; Johannessen & Fuglseth, 2016).

2.9.2 Application

Designing functional front-end systems for the business requires both business insights as well as a good understanding of the design application's capabilities. Specific attention needs to be placed on how the information will be presented within the system to the end users to ensure that it is easy enough to navigate and locate the required business information, while also ensuring that the results are in a format that is user-friendly and consumable by the business for their decision making processes (Aljarba et al., 2019; Eriksson & Ferwerda, 2019; Immhoff & White, 2011).

2.9.3 Data

In recent years a new trend of Big Data has emerged and with this trend comes additional complexities such as storage due to the sheer size of the data being produced and consumed within the business (Ukhalkar et al., 2020). The power users need to deliberately focus on this matter during the design phase of their ETL processes to ensure that the data is in a consumable state for the front-end systems to ensure that their efficiencies are not hindered due to the size and complexity of the data. Once the data has been loaded into the front-end systems, the power users need to then

ensure that information is in a presentable state for the casual user to ensure that decisions can be made timelessly and without much effort (Ain et al., 2019; Alpar & Schulz, 2016).

2.9.4 People

As SSBI is focused on providing the casual BI user with the ability to service their own information needs via front-end systems, a key challenge present in SSBI which is hindering its implementation and adoption is ensuring that the casual user has adequate training and knowledge of the front-end system to ensure that they are capable of utilising the tools to their fullest potential without the need of a BI analyst (Aljarba et al., 2019; Daradkeh & Al-Dwairi, 2017; Jooste et al., 2018).

2.10 The use of Business Intelligence within the Banking Industry

The banking industry is continuously evolving and is at the forefront of innovation and development in terms of technology and the use of the information produced by the technologies (Moro et al., 2015). Important and evolving areas within the banking section cover a number of core functions such as credit risk and analysis, customer relationship management, e-Banking which refers to banking online via the various products available, banking regulations, fraud detection, policy development, and competitor analysis (Moro et al., 2015; Owusu, 2017; Rezaie et al., 2017; Wiradarma et al., 2017). Business Intelligence and its focus on producing and providing key information within the banks, plays a key role in the industry with its ability to present structured information to the decision makers within the bank.

With the introduction of internal and external data sources, the banking industry is able to bolster its analyses of historical events allowing them to predict future outcomes while tracking the current happenings against their predictions. Representing this key information within reporting dashboards and allowing the end-users to view and extract the information as and when required is pinnacle to the success of the various areas within the bank (Pal & Brar, 2018; Rezaie et al., 2017). Other than the usual executive and performance-related reporting, other areas within the banking industry have also started to realise the benefits of employing BI and SSBI within their daily functions. Areas such as those managing customer complaints are able to pinpoint “burning” areas causing angst within the market by presenting key factors related to the complaints to the business such as specific times of days, location of the complaint (is there a specific geographical location that is experiencing issues with banking functionality), banking products to the business ensuring that they are able to investigate and solve the issue before it escalates to a greater scale (Prakash Verma & Sharma, 2021). Operational areas such as the debt collection (more commonly known as Collections) areas are also able to recognise the benefit of SSBI by allowing the operational staff to make use of reporting dashboards to extract their individualised detailed work item report. This functionality will reduce the need for the managers to manually draw up work item reports for each staff while ensuring that they are updated periodically. The operational managers are able to focus on managing and ensuring that the work is being completed while also having the ability to view the performance states of each analyst allowing for adjustments within the business as needed (Pal & Brar, 2018; Prakash Verma & Sharma, 2021).

Business intelligence in both its formats (traditional and SSBI) benefits the banking industry from a multitude of angles. Executive and managerial reporting for decision-making is its core output to ensure focus is achieved on each function within the bank while an added benefit being realised by the banks relates to the operational aspect of SSBI and its ability to allow the junior staff members to drive their own successes in part improving the business performance.

2.11 Information Technology Adoption Frameworks

A variety of different frameworks have been formulated over the years in order to examine the phenomenon of adoption within the information technology (IT) field (Hatta et al., 2015; Koul & Eydgahi, 2017; Oliveira & Martins, 2011). Based on the reviewed literature, the most extensively utilised adoption frameworks are: 1) the technology acceptance model (TAM) formulated by (Davis, 1985), 2) diffusion on innovation (DOI) formulated by (Rogers, 1995), 3) the technology-organisation-environment framework (TOE) formulated by (Tornatzky & Fleischer, 1990), 4) unified theory of acceptance and use of technology (UTAUT) formulated by (Venkatesh et al., 2003), 5) theory of planned behaviour (TPB) formulated by (Ajzen, 1985), 6) the PC utilisation model (MPCU) formulated by (Thompson et al., 1991).

These frameworks can be grouped at a high level into two categories, namely those which examine adoption at an individual level and those which examine adoption at an organisational level (Hatta et al., 2015; Oliveira & Martins, 2011). Organisational level frameworks are focused on constructs which relate to and can impact the organisation as a whole such as the organisations operating environment, the technology currently being used within the organisation as well as the organisation itself and how technology will be incorporated into the organisation. The frameworks grouped into the Individual level category concentrate on the adoption of the technology by the individual in question with focal points being the presentation of the technology to the individual (de Waal & Budree, 2022; Ilin et al., 2017; Koul & Eydgahi, 2017). Figure 1 provides a graphical representation of these categories while also highlighting the selected framework for this research.

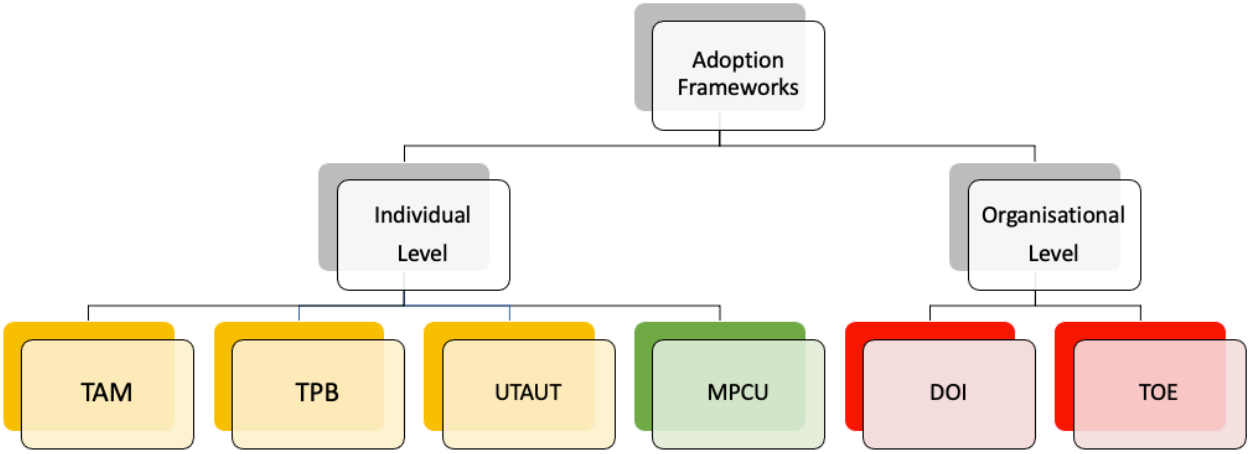

Figure 1: Adoption frameworks split

Identifying a framework which would be best suited for the research depends on the research problem, questions, as well as the researcher's own belief system (Grant & Osanloo, 2014). As this research is based on the

individual and how the various human factors affect their adoption of SSBI, all the frameworks relating to a group level have been excluded from the selection process. The remaining frameworks will be briefly discussed in the below section.

2.11.1 Technology Acceptance Model (TAM)

One of the most popular adoption frameworks is the TAM framework which has been used in a variety of IT studies (Koul & Eydgahi, 2017; Li, 2010). The TAM model was developed to determine which design factors and issues could potentially hinder the user's acceptance and adoption of the technology products (Koul & Eydgahi, 2017; Li, 2010). Due to the fact that the research is not looking at the design aspects related to the reporting models, in particular, this framework will not be used.

2.11.2 Theory of Planned Behaviour (TPB)

Another greatly utilised framework is TPB which predicts the behaviour of an individual within a voluntary situation (Koul & Eydgahi, 2017; Li, 2010). TPB assumes that in a given situation, the individual will make a rational decision that benefits themselves in the long run (Koul & Eydgahi, 2017). Due to the fact that the research is not looking at the behaviour intention to make use of the SSBI, this framework will not be used.

2.11.3 Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT is a combination of the various constructs identified in eight past frameworks in order to evaluate the intended use of technology by an individual (Alkhwaldi & Kamala, 2017; Gunasinghe et al., 2019; Li, 2010). Although UTAUT has been successful in explaining adoption in a number of different technologies, its main weakness is the size of the model and the number of constructs included (Alkhwaldi & Kamala, 2017; Alomary & Woollard, 2015). Due to the fact that the research is not looking at the design aspects of the reporting models as well as the behaviour intention to make use of the system, this framework will not be used.

2.11.4 Model of PC Utilisation

The model of PC Utilisation was developed in 1991 and it looks at the acceptance level of PC use based on the participant's human behaviour and attitudes. (Thompson et al., 1991) claims that "behavior is determined by what people would like to do (attitudes), what they think they should do (social norms), what they have usually done (habits), and by the expected consequences of their behavior" (p. 126). The framework focuses on investigating the actual behavioural influences that affect the use rather than determining the intention to make use of the information technology (Alkhwaldi & Kamala, 2017; Gunasinghe et al., 2019; Taherdoost, 2018). For this reason, the model of PC Utilisation has been selected for this research in order to answer the research questions proposed in section 1.4.

2.12 Theoretical Framework

The model of PC utilisation as depicted in Figure 2 has six constructs that determine the user's acceptance of PCs (Alomary & Woollard, 2015; Li, 2010). Although the model refers to the utilisation of personal computers (PCs) as the final dependent variable, the theoretical nature of the model allows for it to be applied in the acceptance of various

forms of information technology and its applications, therefore the model has been adapted to the adoption of SSBI (Alkhwaldi & Kamala, 2017). Each of the six constructs will be briefly discussed below.

2.12.1 Job Fit

Job fit relates to the comfort level at which an employee believes that the system will improve their abilities within their jobs (Andreas, 2012; Dawley et al., 2010; Thompson et al., 1991). The requirement for BI within a business is to monitor and identify potential success or challenges within the environment (Johannessen & Fuglseth, 2016). SSBI benefits a business by providing the various end-users with the level of control that is required in order to become self-reliant and independent from the BI departments and analysts (Lennerholt et al., 2018; Lennerholt & van Laere, 2019). Therefore, we are able to argue that:

$\boldsymbol{H_1}$: *Job fit has a significantly positive influence on the adoption of SSBI.*

2.12.2 Complexity

Complexity refers to the degree of difficulty with which an individual finds the system in order to achieve their desired outcomes (Andreas, 2012; Thompson et al., 1991). SSBI reporting models are not always constructed in such a way that it makes it easy for the various end-users types to extract the required information (Popovič, 2017). In order to alleviate the angst faced within the business, the front-end SSBI reporting models should be designed in such a way that it promotes easy access to the required information at the right times (Aljarba et al., 2019). Therefore, the following can be argued:

$\boldsymbol{H_2}$: *Complexity has a significantly negative influence on the adoption of SSBI.*

2.12.3 Affect Towards Use

Affect towards use can be defined as the feeling which may be either positive or negative, which individuals experience while making use of the system (Thompson et al., 1991). In a study conducted by Chao (2019) the perceived enjoyment was shown to positively influence the user's satisfaction levels while making use of m-Learning. An emotional aspect is evident when the users make decisions based on technology which needs to be considered during the design phase of the product (Buenaflor & Kim, 2013). Therefore, we can argue:

$\boldsymbol{H_3}$: *Affect towards use will have a significantly positive influence on the adoption of SSBI.*

2.12.4 Social Factors

Social factors refer to the degree of influence others within the business might have on the individual to make use of the system (Andreas, 2012; Thompson et al., 1991). Users which have been trained and have been given the relevant access rights should be encouraged and empowered to make use of the systems (Alpar & Schulz, 2016). According to Gudfinnsson & Strand (2017), the lack of managerial support in terms of the adoption of the BI systems was their largest barrier, this sentiment has been echoed by Antoniadis et al. (2015), stating that by clearly expressing

the importance and strategic reasons for the adoption of the system will alleviate the angst within the business. Therefore, we can argue:

$\boldsymbol{H_4}$: *Social factors will have a significantly positive influence on the adoption of SSBI.*

2.12.5 Long-term consequences

Long-term consequences are a forward-looking event in which an individual is able to foresee the future benefits that making use of the system will have on them and their current working processes (Thompson et al., 1991). In order for a business to grow substantially, the various business divisions are required to focus on their core responsibilities (Olszak, 2016). By allowing the power and IT users to focus on their responsibilities of designing effective theme based reporting models, the end users will be able to efficiently and effectively extract information to drive the decisions within the business (Aljarba et al., 2019; Passlick et al., 2017; Weiler et al., 2019). Therefore, we can argue:

$\boldsymbol{H_5}$: *Long-term consequences have a significantly positive influence on the adoption of SSBI.*

2.12.6 Facilitating Conditions

Facilitating conditions is defined as the degree to which the system has been structured in order to assist the individuals' successful use (Andreas, 2012; Thompson et al., 1991). It was found by Stjepić et al., (2021) that by making use of various cloud and mobile solutions, the enterprise can overcome the challenges caused by infrastructural complexities, making it easier for the users. Further, it has also been shown that by ensuring that the staff have been adequately trained, their comfort levels while using the system will increase. Therefore, the following can be argued:

$\boldsymbol{H_6}$: *Facilitating conditions will have a significantly positive influence on the adoption of SSBI.*

2.12.7 Hypothesis Summary

Hypothesis Number	Definition
H_1	*Job fit has a significantly positive influence on the adoption of SSBI.*
H_2	*Complexity has a significantly negative influence on the adoption of SSBI.*
H_3	*Affect towards use will have a significantly positive influence on the adoption of SSBI.*
H_4	*Social factors will have a significantly positive influence on the adoption of SSBI.*
H_5	*Long-term consequences have a significantly positive influence on the adoption of SSBI.*
H_6	*Facilitating conditions will have a significantly positive influence on the adoption of SSBI.*

2.13 The research Model

Based on the model of PC utilization framework as developed by (Thompson et al., 1991) as well as the discussion on the constructs in the above section, we are able to present an adapted version of the research model within Figure 2 below.

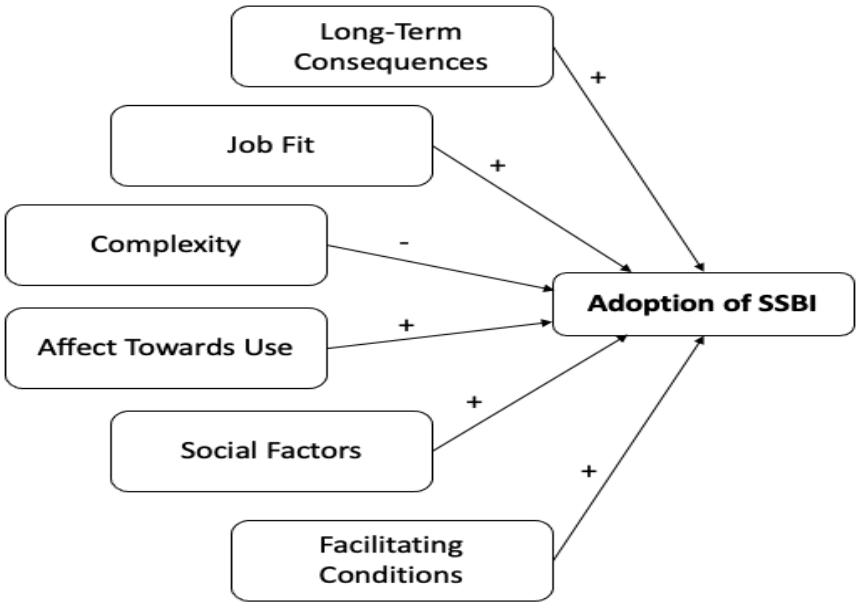

Figure 2: The Model of PC Utilization adapted from (Thompson et al., 1991)

2.14 Literature Review Summary

Although the importance of the information generated within the BI departments have only increased in its need. It is clear from the literature that the traditional form of BI was bound to be rethought and redesigned. The introduction of SSBI within the toolkit available to BI departments has provided a solution to the requirement to get information to the decision-makers quicker. Not much has changed in terms of the methodologies from which SSBI has spouted, however, conceptually there has been a substantial shift in the way the BI departments produce information for the business. Considerations on how the information is produced, stored, and ultimately displayed to the end user has been a key objective of SSBI. With each of these considerations, came new challenges relating to the type of technology to use, how to format the data and most importantly, how to get the decision-makers to adopt and utilise the tools available. Based on the literature review, it is apparent that how we investigate the adoption of SSBI in the past has been skewed towards a business outlook. This is partly understandable, since it is a new concept that the business needed to integrate the methodology within the business. However, to ensure that SSBI is successfully integrated within the business, we need to study the humanistic side of the adoption. This means that focus needs to be placed on understanding how specific aspects relating to the individuals adopting SSBI affect its take-up. This aspect of the adoption process was found to be a significant gap in the literature and focus was deemed necessary. During the literature review, the model of PC utilisation was believed to be the best fit for this task. Testable hypotheses were then formatted based on the literature in conjunction with the research questions and will from part of the remaining research paper with the aim to provide an answer to whether human factors play any role in the adoption of SSBI.

Chapter 3: Research Design and Methodology

3.1 Introduction

Conducting efficient research requires the researcher to follow a well-defined and systematic approach. The research design should provide an overview of the guidelines, processes, and procedures which will be followed throughout the research. Selections made during this phase of the research will have an impact on how the research proceeds further (Crowther & Lancaster, 2008; Saunders et al., 2009). These selections will be discussed in the sections below.

3.2 Research Philosophy

The selections made during the philosophical phase of the research will have significant impacts on the possible research strategies and methodology that are available for use by the researcher (Crowther & Lancaster, 2008). These selections reflect the researchers' beliefs and assumptions during the knowledge development phase of the research as well as how the researcher expects the phenomena to exist within the world. The researchers' beliefs and assumptions stem from fundamental questions such as "What is it that we are trying to observe?", "How does the phenomena exist within the world?" and "How is the knowledge created by the knower?" (Guba & Lincoln, 1994; Saunders et al., 2009). The two main philosophical assumptions relate to ontology and epistemology which will be discussed in sections 3.2.1 and 3.2.2 below and will shape the building blocks of the entire research methodology which is to follow.

3.2.1 Ontology

Ontology points out how the researcher views reality and the assumptions that are therefore constructed (Saunders et al., 2009). Although there are various forms of ontologies, each researcher will have their own personal ontological perspective which will shape the way in which their research is conducted and interpreted (Crowther & Lancaster, 2008). The two main ontological perspectives are objectivism and constructivism. Objectivism believes that the phenomena being researched will have a singular truth which is not influenced by the research process being carried out (Orlikowski & Baroudi, 1991; Saunders et al., 2019; Vrasidas, 2000). This assumption indicates that the information which is to be observed during this research is already in existence and is ultimately held by the experiences and knowledge of the respondents to the research (Orlikowski & Baroudi, 1991). Constructivism on the other hand postulates that knowledge is created by experiences and is independent of the people involved in its overall creation (Orlikowski & Baroudi, 1991; Saunders et al., 2019; Vrasidas, 2000). Constructivism, therefore, focuses on how the respondents place meanings to their real-world experiences relating to the phenomena (Orlikowski & Baroudi, 1991).

This research aims to examine the human factors that ultimately affect the adoption of self-service business intelligence (SSBI) within the banking sector of South Africa by testing the theory as formulated in the MPCU framework. This research does not plan to influence the adoption of SSBI within the banking sector during the research phase but merely aims to measure its current state and report on the influences that human factors have on its ultimate adoption in order to better understand the adoption of SSBI phenomena. Therefore, the research will adopt an *objective* ontological stance.

3.2.2 Epistemology

An epistemological perspective refers to how the researcher deems knowledge to be created, evaluated and transferred amongst others within the world (Orlikowski & Baroudi, 1991; Saunders et al., 2019). Although there are a number of different types of epistemological perspectives that can be applied within research, there exists an underlying connection between the previously selected ontological stance and the subsequent epistemologies which are available for use within the research (Aliyu et al., 2014). Orlikowski & Baroudi (1991) postulates that within the field of information systems (IS), three predominant epistemological stances are applied, namely positivism, critical realism, and interpretivism. Each one of these stances will be discussed briefly below.

3.2.2.1 Positivism

Positivism refers to a discoverable nature in which reality is self-governing and unaffected by either of the human participants (the creator or the observer) of reality. The laws which govern the existence of a particular reality are applied unchanged to all participants (Aliyu et al., 2014; Berryman, 2019; Saunders et al., 2019).

A positivist would usually ask a question from which statistics can be acquired and analysed in order to identify potential relationships and patterns which can then either confirm or refute the research question(s) and hypotheses initially asked (Berryman, 2019; Ryan, 2018; Saunders et al., 2019). As positivism believes in quantifiable observations, there are a number of research methods regularly associated with it such as experiments (both within the field and within a laboratory) and quantitative research (Aliyu et al., 2014; Ryan, 2018).

3.2.2.2 Interpretivism

Interpretivism argues that knowledge is subjective to the observer and is based on the experiences and interactions that the participants have gone through up to that point. In short, there is no one set of truths which can be applied to the phenomena and meaning associated by the participant(s) is where the knowledge is created (Aliyu et al., 2014; Berryman, 2019; Orlikowski & Baroudi, 1991; Ryan, 2018; Saunders et al., 2009). As interpretivism focuses on the meaning within the research, it is usually associated with qualitative and exploratory research (Aliyu et al., 2014; Saunders et al., 2009).

3.2.2.3 Critical Realism

Critical realism is the so-called middle ground between positivism and interpretivism (Saunders et al., 2009). Critical realists do not argue the existence of reality and knowledge but instead postulate that the social systems and structures in which the society exists, alter how the knowledge is created and transferred (Balarabe Kura, 2012; Orlikowski & Baroudi, 1991; Saunders et al., 2009).

3.2.3 Epistemological Selection

Given the objectivistic ontological stance to examine the human factors that affect the adoption of self-service business intelligence within the banking sector of South Africa. This research intends to make use of the Model of PC

Utilisation framework to formulate testable hypotheses that can be used to answer the overall research question(s) as denoted in section 1.4 of this document. Therefore, the proposed research will adopt a *positivistic* stance.

3.3 Research Purpose

The purpose of conducting research can be grouped into three categorisations namely exploratory, descriptive and explanatory with a large portion of academic research falling within the explanatory category (Bhattacherjee, 2012; Saunders et al., 2009).

Exploratory research often involves new areas of interest where details such as the size or feasibility of the phenomenon are unknown to the researcher and can be used as a guide for further, more in-depth studies. Descriptive research evolves detailed observations of the phenomena which can be replicated within future research or observations in order to describe the behaviour of the population being observed. Explanatory research is used to understand and provide an explanation for a particular phenomenon based on a highly structured approach and can be used to examine the cause-and-effect relationships between the various constructs being observed.

The purpose of this research aims at examining the relationship between the human factors and the adoption of SSBI with the use of hypotheses. Therefore, an *explanatory* research method will be adopted.

3.4 Research Approach

Generally, there are two approaches while conducting academic research namely a deductive and inductive approach. Deductive research is structured in such a way that it starts with an existing theory from which hypotheses or propositions are formulated. This theory is then tested against the data collected within the research to either confirm or disprove the proposed hypotheses or propositions within the research (O'Reilly, 2012; Saunders et al., 2019). Inductive research on the other hand is the inverse of deductive, whereas little to no assumptions are made at the start of the research which allows for a theory to naturally formulate from the data which has been collected within the research process (O'Reilly, 2012; Saunders et al., 2019).

As the proposed research aims at formulating hypotheses based on a known theoretical framework namely, The Model of PC utilisation model in order to achieve an answer to the research questions posted in section 1.4 above, therefore the proposed research will adopt a *deductive* approach.

3.5 Research Strategy

Research is generally conducted from one of three different strategies, namely qualitative, quantitative, or a mixed-method approach (Saunders et al., 2019). Qualitative research is a subjective method to research where interviews are conducted to obtain the respondent's opinions or attitudes regarding the phenomena, while quantitative research is based on the collection of data which can be statistically analysed in a rigorous manner to obtain an outcome to the posed questions (Kothari, 2004). Mixed method research on the other hand is a combination of both the quantitative and

qualitative research methods, allowing the researcher to make use of the strengths of both methods in an attempt to postulate a concise answer to the research question(s) (Fetters et al., 2013; Olivier, 2017; Venkatesh et al., 2013).

A *quantitative* approach was selected for this research coupled with a *questionnaire survey strategy* as this strategy allowed for the collection of a larger quantity of data relating to the independent and dependent variables of the proposed framework in sections 2.12 and 2.13 above. This data was then used to examine the relationships between the variables in order to answer the research questions posted in section 1.4 (Bhattacherjee, 2012; Saunders et al., 2009).

3.6 Research Timeframe

The timeframe in which research is conducted is usually one of two methods, namely cross-sectional or longitudinal. Longitudinal research is conducted over multiple points in time, therefore, allowing the researcher to observe the phenomena from different scenarios such as before and after a change in a process has taken effect. Longitudinal studies are interested in observing whether there has been a particular affected on the research population over time, while cross-sectional research is conducted to observe the phenomena at a particular point in time usually conducted over weeks or months. (Bhattacherjee, 2012; Saunders et al., 2009; Sekaran, 2016).

This research will be conducted within the banking sector of South Africa during 2022 for a specific period in which both the dependent and independent variables of the phenomena will be measured. Due to the academic nature of the proposed research as well as the time allotted to the students by the university in order to complete the Master's programme a *cross-sectional* research timeframe will be employed in which a snapshot of the phenomenon will be observed.

3.7 Population and sampling

Collecting data from the entire population of interest is not feasible in many cases due to a variety of reasons such as access, time and costs. Therefore a representative subset of the target population called a "Sample" should be selected in order to derive the statistical inferences about the said target population (Bhattacherjee, 2012; Saunders et al., 2009). By narrowing the research down to a selected sample of participants the researcher has the ability to increase the detail of the information collected while also saving on research time and overall costs (Saunders et al., 2009)

Three specifically designed steps have been identified to assist researchers in making an appropriate sample selection within their research. These steps are as follows: Firstly, the target population for the research needs to be identified. According to Bhattacherjee (2012), the target population relates to the group of people or cases which you are interested in studying. The second step is the selection of a sample frame which according to Taherdoost (2016) is a specific list of people or cases from which a sample can be drawn. Lastly is narrowing down the selection to the actual sample group that will be incorporated within the research from which the inferences regarding the population will be made (Bhattacherjee, 2012; Saunders et al., 2009; Taherdoost, 2016).

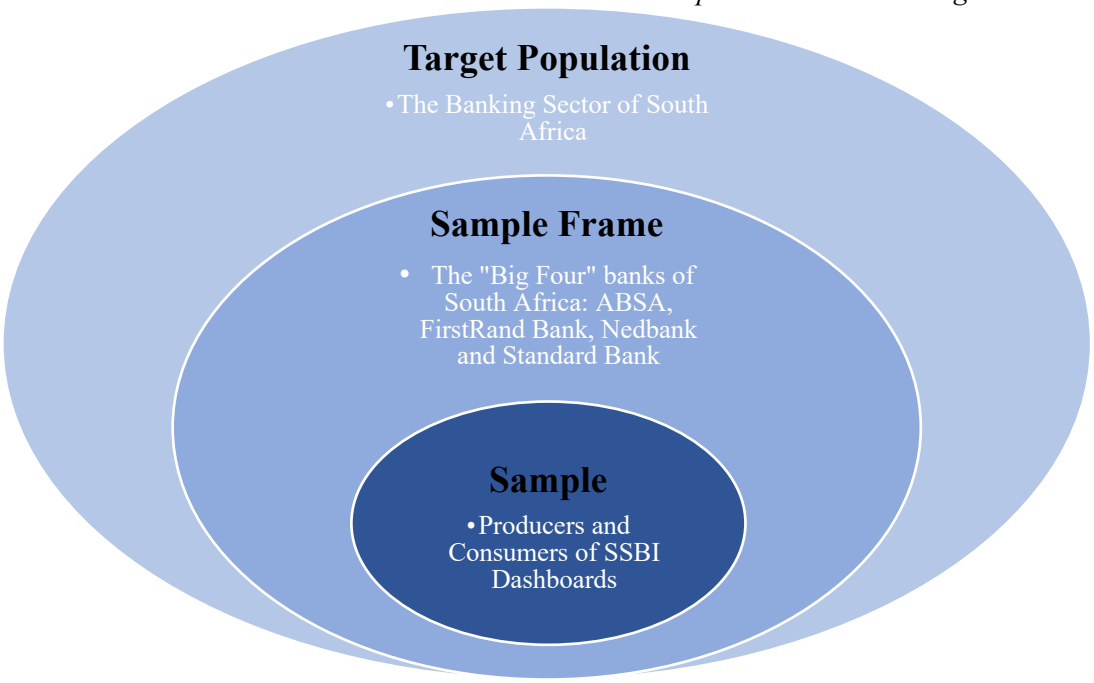

Figure 3: Sample population breakdown

For the purpose of this research, the following selections have been made based on the discussion points above. To be as representative as possible, the targeted population has been identified as the Banking Sector of South Africa, while the sample frame has been narrowed down to the "Big Four" banks of South Africa, namely: ABSA, FirstRand Bank, Nedbank and Standard Bank. Lastly, the sample population has been identified as both the decision-making consumers and producers of self-service business intelligence or business intelligence reporters as represented by Figure 3 above.

3.7.1 Sampling Technique

Due to the deliberate nature and time constraints of this research, a combination of two non-probability sampling methodologies has been selected. Judgmental or otherwise known as purposeful sampling will be primarily utilised due to its deliberate nature to extract relevant information from a focused cohort of participants that share a particular trait required for this research. Together with the judgemental sampling technique, the research will employ the snowball sampling technique by calling on the participants identified during the judgemental sampling to forward the online survey to other participants or colleagues that meet the requirements of the sample population (Kothari, 2004; Saunders et al., 2009; Taherdoost, 2016). By making use of the initial demographic information collected, any participant that falls outside of the defined scope of the research will be excluded from the results section of the research.

3.7.2 Sample Size

The three main considerations when determining the sample size of this research were the sampling techniques employed, the total population size, and the research timeframe allowed in order to complete the master's course.

By making use of non-probability sampling techniques, the size of the sample should be based on the research questions which are to be answered, unlike the probability sampling techniques where strict rules and formulas are

applied. In an attempt to determine an estimated acceptable sample size, a quick internet search showed that the "Big Four" banks employ approximately 174,000 staff members as shown in Table 3 below (Battle of the Banks: South Africa's Big 5 Banks Compared, 2019). As mentioned in chapter 3.6, a specific period during 2022 was demarcated for data collection in order to prepare and complete the thesis. Due to these reasons, a confidence level of 90% was selected in order to ensure that an acceptable sample size can be obtained for the research.

Bank Name	# of Employees
ABSA	40,856
FirstRand Bank	48,780
Nedbank	31,277
Standard Bank	53,178
Total (A)	**174,091**

Table 3: "Big Four" banks employee numbers

Population assumption	Size calculation (A * n%)	Required Sample
2.5% of Group	4,352	257
5% of Group	8,705	265
10% of Group	17,409	269

Table 4: Population Size estimate

Based on the population size table as presented by (Adam, 2020) once the size of the target population gets to around 50,000 and greater the required sample size plateaus regardless of the percentage of your confidence level. As the total banking population as stated in Table 3 above is around 174,000 therefore indicating that any sample size above 270 would be sufficient. It is, however, irrational to believe that the total population of the "big four banks" create or make use of SSBI or BI. By assuming a conservative range estimate of 2.5% to 10% of the target population being within our target range, a population size of around 4,352 to 17,409 is observed. Making use of these estimated numbers, the sample size was calculated at a confidence level of 90% with a 5% margin of error via an online sample size calculator and provided in Table 4 (Sample Size Calculator, n.d.).

3.8 Data Collection

3.8.1 Research Instrument

A self-administered online questionnaire was selected as the most appropriate research instrument for this research, due to the fact that it can reach a large contingent of the sampled population in a relatively short period of time. The research instrument is at a core guided by the selected research philosophy and strategy that has been employed within the study. According to Saunders et al. (2009), explanatory studies will generally make use of questionnaires as it allows the researcher to examine the relationships held among the independent and dependent variables. While Kothari (2004) argues that questionnaires have great importance when the research is faced with obstacles such as short time frames and large amounts of data collection needs.

The online questionnaire was formulated based on an in-depth analysis of the literature in order to answer the proposed hypotheses in section 2.12.7. The questionnaire made use of both nominal (in terms of categorised groupings that the participant can select from) and ordinal (in the form of ranking selection options) scales to collect information. Making use of closed-ended questions, the questionnaire allows the respondents to complete the survey easier while also allowing for their responses to be analysed and compared due to the predetermined answering structure (Saunders et al., 2009; Sekaran, 2016). The nominal scales were primarily used within section one of the questionnaire while sections two to eight made use of ordinal scales in the form of a five-point Likert scale where 1 would represent the highest value and 5 represented the lowest value. A draft example of the questionnaire has been supplied in Appendix C – Questionnaire. The eight sections of the questionnaire were as follows:

- Section one focused on collecting high-level information relating to the **Demographics** of the participant.
- Section two measured items relating to the **Job Fit** construct.
- Section three measured items relating to the **Complexity** construct.
- Section four measured items relating to the **Affect towards use** construct.
- Section five measured items relating to the **Social Factors** construct.
- Section six measured items relating to the **Long-Term Consequences** construct.
- Section seven measured items relating to the **Facilitating Condition** construct.
- Section eight measured items relating to the **Adoption of SSBI** construct.

3.8.2 Reliability and Validity of the Research Instrument

By measuring the reliability and validity of the research instrument, the researcher is able to provide evidence that a sufficient level of rigour has been adhered to during the development of the instrument. The evidence can be presented as well-defined consistent procedures that were followed within the research, therefore ensuring that the research community is able to replicate the processes followed while also reducing the risk of coming to an incorrect conclusion (Saunders et al., 2009; Sekaran, 2016).

3.8.2.1 Reliability

Reliability refers to how consistent and reliable a set of variables are when measuring a particular phenomenon. Principally, it refers to how consistent would the results of the research be if multiple attempts were conducted by other researchers (Bolarinwa, 2015; Hair et al., 2010; Saunders et al., 2009). In order to test the reliability, two separate tests can be conducted, firstly the internal consistency of the models' constructs should be tested using the Cronbach's alpha test which measures how consistent the responses to the particular questions are. The results of the Cronbach test will then be measured against the acceptance levels as represented in Table 5 below to indicate the level of reliability achieved (Gliem & Gliem, 2003; Hair et al., 2010). Secondly, an inter-item correlation can be conducted in order to test the correlation of the various items within each construct of the model, the values of each construct should be within an acceptable range of 0.15 to 0.5 (Hair et al., 2010).

Cronbach's alpha results	Acceptance level

$\alpha \geq 0.9$	Excellent
$\alpha \geq 0.8$	Good
$\alpha \geq 0.7$	Acceptable
$\alpha \geq 0.6$	Questionable
$\alpha \geq 0.5$	Poor
$\alpha < 0.5$	Unacceptable

Table 5: Cronbach's alpha acceptance levels (Gliem & Gliem, 2003)

3.8.2.2 Pilot Study

A pilot study is sometimes overlooked in research however, it is an important part of research projects and can be viewed as a test run of the data collection and analysis process prior to the actual research project. A pilot study is intends to identify whether the questionnaire is understandable while also identifying possible gaps and concerns within the questionnaire, therefore, increasing the validity and reliability of the information being collected within the research (Bhattacherjee, 2012; Kothari, 2004; Saunders et al., 2009). For the pilot study, a group of purposively selected participants made up of colleagues and experts within the BI field were selected for their insights relating to the subject matter and survey process. Each participant was provided with a link to the survey and a timeframe in which they needed to complete the pilot study with a request to highlight any questions, inconsistencies, or areas of concern that they might have observed. In the event that any concerns were raised within the pilot study, the finalised questionnaire would be amended before commencing with the data collection process (Bhattacherjee, 2012; Saunders et al., 2009).

3.8.2.3 Validity

Validity refers to how accurately the research instrument measures what it is intended to measure (Hair et al., 2010; Saunders et al., 2009). In order to test for the validity of the research numerous statistical analyses could be conducted such as Bivariate correlational analysis and factor analysis (Bhattacherjee, 2012). Each of these methods represents how closely each of the measurements compares to one another within the construct. According to Bhattacherjee, (2012), while comparing the values of two constructs, a high correlation within the constructs confirms convergent validity (the measures are similar in nature) while a low correlation subsequently demonstrates discriminant validity (the two constructs are not alike). Table 6 below demonstrates the acceptance levels associated with the Kaier-Meyer-Olkin (KMO) results achieved while conducting a factor analysis (Halim & Ishak, 2014).

Kaier-Meyer-Olkin (KMO) results	Acceptance level
$KMO \geq 0.9$	Excellent
$KMO \geq 0.8$	Good
$KMO \geq 0.7$	Acceptable
$KMO \geq 0.6$	Questionable
$KMO \geq 0.5$	Poor
$KMO < 0.5$	Unacceptable

Table 6: Kaier-Meyer-Olkin (KMO) acceptance levels (Halim & Ishak, 2014)

3.8.3 Data Collection Process

The data collection process commenced upon the receipt of the successful clearance certificate from the University of Cape Town (UCT) ethics committee which indicated the approval of the research design and instrument to be used within the research.

The online questionnaire was created using Google Forms due to its relative ease of use from both the developer's and user's points of view. The questionnaire was made up of two parts. Part One is the consent form which included a short background of the researcher and briefly explained the purpose and objective of the research project while also highlighting the approval from the UCT ethics committee and ensuring the participants that the data collected in the questionnaire will only be used within the research and that it is strictly voluntary as shown in Appendix B – Consent form. Part Two was the actual questions relating to the constructs as presented in section 3.8.1 as shown in Appendix C – Questionnaire. Before each participant could proceed with the questionnaire, they were required to indicate whether they consent to the participation. If the participant did not give consent, the record was captured, and the participant could not proceed further with the questionnaire.

A link to the Google Forms questionnaire was distributed to the selected sample via email and social medial platforms such as Facebook, WhatsApp, and LinkedIn. To increase the reach of the research, an additional link was posted on topic-specific groups and pages within Facebook and LinkedIn, therefore allowing additional participants to voluntarily partake in the research. Figure 4 below represents the high-level process followed to ensure the successful collection of the data.

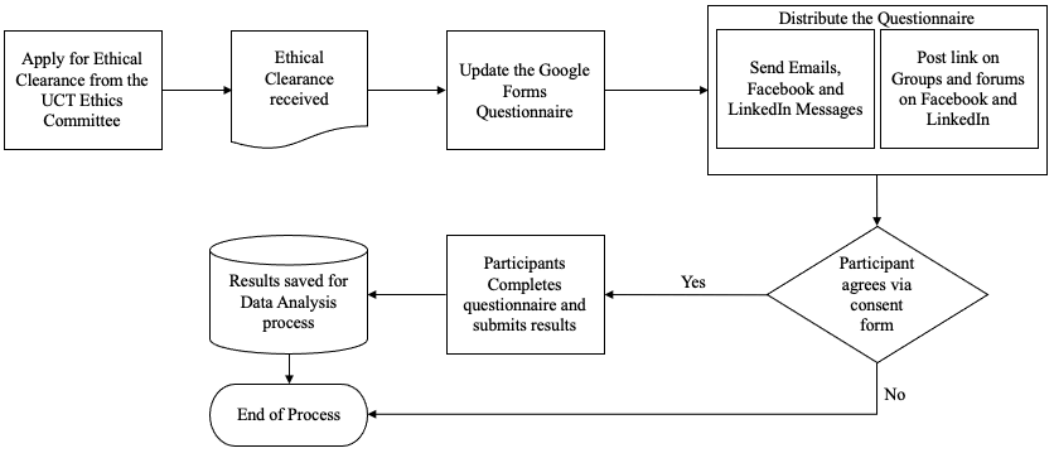

Figure 4: High-level Data Collection Process Flow

3.9 Data Analysis

During the process of statistical analysis, the goal should relate to more than just producing a statistical result but rather analysing the results and critically determining whether the results answer a deeper fundamental question. Therefore, the analysis process should be shaped on an ongoing basis as you uncover additional findings within the results (Albers, 2017).

3.9.1 Data Preparation and Clean-up

The data collected within this study was analysed using quantitative data analysis methods. The first step of this process was extracting the information captured during the survey process and transferring the information to an electronic format which could be consumed and processed within the SPSS v28 analytic tool (Jones & Hidiroglou, 2013). During the data preparation and clean-up phase, which according to Jones & Hidiroglou (2013) can be seen as the initial data analysis phase, the results could be manually interrogated within Microsoft Excel in order to identify any potential data anomalies or errors which would need to be addressed before the commencement of the data analysis process (Hair et al., 2010).

3.9.2 Data Analysis Process

As within the data instrument, the data analysis process has been split into different sections in order to focus on each of the methodologies utilised as represented in Table 7 below.

Analyses	Type of Analysis	Analytical Methods
Section 1	Demographical Representation	Age Grouping
		Gender Grouping
		Employer Name
		Education Level
		Employment Level
		Working within a BI department?
		Heard of SSBI before?
		How often is SSBI used?
Section 2	Reliability Testing	Cronbach's alpha test
Section 3	Factor Analysis	With the use of Varimax Normalised rotation method
Section 4	Distribution Testing	Test for Normality
	Hypotheses Testing	Ordinal Regression Analysis

Table 7: Analytical Methods to be applied

The results from section one will build a mental picture of the sampled population while providing valuable insights into how the population reacts to the various constructs within the framework. Section two of the data analysis process focuses on the fundamental structure of the data which will ultimately shape the analysis methodologies going forward within the research. Section three is where we conduct factor analysis in order to determine the construct validity while identifying the relationship amongst the constructs and reducing the data variables, indicating their importance levels within each construct (Bhattacherjee, 2012). Lastly, section four covered the hypotheses testing processes with the use of multiple regression analysis techniques.

3.10 Ethical Considerations

Ethics relates to the moral choices we make throughout all aspects of our life and relationships (Saunders et al., 2009). To ensure that the highest level of ethics is upheld, the researcher has submitted the research instrument and all related information to the universities ethical committee for evaluation. All observations identified within this process were treated with the utmost importance and implemented throughout the research project. The ethical approval form has been included in Appendix A – Ethics Approval of this document. Additional project-specific considerations have been discussed below.

3.10.1 Confidentiality and Informed Consent

Before the commencement of any data collection, the participants are required to read and agree to the voluntary participation of the questionnaire. Within the consent form as provided in Appendix B – Consent form, the scope of the research together with the details of the researcher, research supervisor and the university have been provided.

Each participant was further reminded that participation in the research is completely voluntary and that they have the right to withdraw at any stage of the research before the final submission of the results. Although each participant's identity has been kept strictly anonymous during the data collection process, additional high-level information such as demographics, education and employment would be disclosed in order to be used in the analysis of the research.

3.10.2 Institution protection

As this research was conducted across the “Big Four” banks of South Africa, great care was taken to ensure that any information relating to the banks and their practices that could potentially be extrapolated had been generalised within the data collection, storage, and findings of the research.

3.10.3 Data Handling and Storage

The data collected during this research has been treated with the highest level of confidentiality. A Data Management Plan was formulated and submitted for approval to the university prior to the commencement of the research. Throughout the research project, version control and backup methodology were employed to ensure that minimal data loss was possible. Each iteration of the data and thesis was password protected and saved to a password-protected cloud-base Microsoft OneDrive server that only the researcher has access to.

3.11 Research Design Summary

The intention of this research project is to examine the human factors that influence the adoption of self-service business intelligence within the banking sector of South Africa. With that in mind, this chapter has provided a concise overview of the research design and methodology utilised within this research; it clearly discusses the chosen philosophical stance adopted for the research which shapes the methods and techniques which were employed within the research. Table 8 depicts a summary of the research design and methodology that guided the research.

Methodology	Approach
Philosophy	Objectivism with a Positivist Stance
Research Purpose	Explanatory
Research Approach	Deductive
Strategy	Survey
Time Frame	Cross-Sectional
Target Population	Banking Sector of South Africa
Sample Population	Consumers and Producers of SSBI/BI within the "Big Four" banks.
Data Collections	Quantitative - Questionnaire
	- Google Forms
	- Closed Questions
Data Analysis	Quantitative
	- Microsoft Excel
	- SSPS v28

Table 8: Research design summary

Chapter 4: Data Analysis and Findings

4.1 Introduction

This study aims to examine the human factors which influence the adoption of self-service business intelligence within the banking sector of South Africa. In order to achieve this result, an online survey was administrated via the research instrument designed in Google forms, refer to Appendix C – Questionnaire for the survey.

The following chapter will provide the high-level demographics collected from each respondent as well as their awareness and use of SSBI reporting models within their workspace. Following the demographic analysis, statistical measures were conducted on the data in order to determine the reliability and validity of the proposed research model while further testing the various hypothesis through the use of the multiple regression models as presented in chapter 2.12 above.

4.2 Data Familiarity, Clean-up, and Coding

A total of 277 responses were initially received during the data collection phase. These responses were then extracted to a Microsoft Excel spreadsheet in order to perform the initial data analysis and clean-up process at a record level by ensuring that the responses meet the required levels to be included in the research (Jones & Hidiroglou, 2013). During this step, an exclusion criterion was performed to remove all responses who did not agree to participate in the research as well as any participant who indicated that they do not work within one of the four included banks of South Africa (i.e. ABSA, FirstRand Bank, Nedbank, and Standard Bank). A total of 20 records were excluded from the research leaving a total of 257 records which met the inclusion criterion.

Response Value	Coded Value	Reverse Coded value
Strongly agree	5	1
Agree	4	2
Neither agree nor disagree	3	3
Disagree	2	4
Strongly Disagree	1	5

Table 9: Response Coding

The data was then subjected to a coding process in which all responses were coded into the numerical format shown in Table 9 as the "Coded Value". Once the data was coded, the Final Dataset was saved and imported into SPSS v28 in order to proceed with the statistical analysis process. An additional coding step was taken to correct the positively or negatively worded questions within research instruments to ensure that the statistical methods were not negatively affected (Bhattacherjee, 2012). Only 4 questions were identified to be affected by the incorrect directional wording and these were questions: 3.7, 4.3, 4.4, and 4.5. These responses were then reversed coded based on the values listed in

Table 9 as the "Reverse Coded Value". Throughout all statistical analyses conducted, the reverse coded values for the above-mentioned questions were used while the original coding was ignored to ensure consistency.

4.3 Demographic Analysis

The following section relates to the high-level demographic information which each participant had to complete while partaking in the survey. The demographic information is used to provide an understanding of the sample population.

4.3.1 Age

Figure 5 below illustrates that there was somewhat of a standard distribution in terms of the respondent's age groupings.

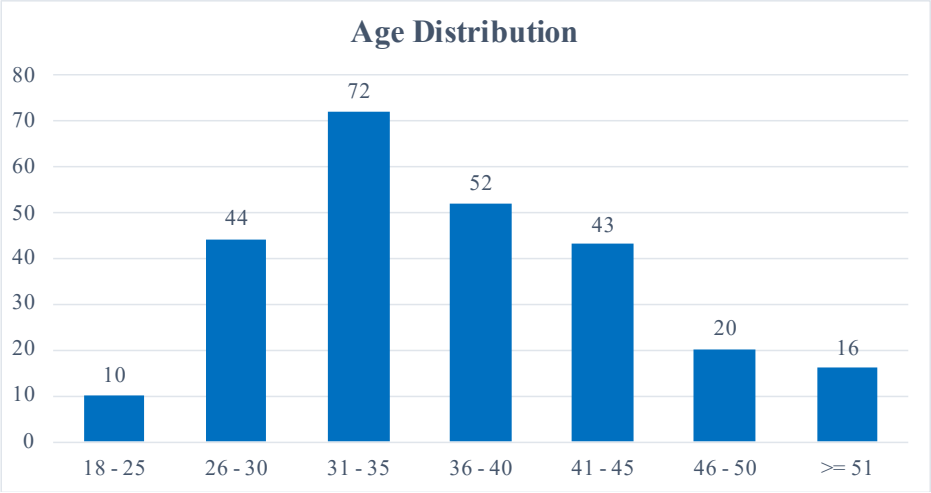

Figure 5: Age Distribution

The majority of respondents were in the age group of 31-35 years (n = 72) with 36-40 years (n = 52) being the second highest group of respondents. The two grouping of 26-30 (n = 44) and 41-45 (n = 43) years were closely matched in the third and fourth highest groups while 46-50 years (n = 20), >= 51 years (n = 16) made up the fifth and sixth groups and lastly 18-25 years (n = 10) being the smallest group of participants.

4.3.2 Gender

The participants were asked to classify themselves into one of the following gender categories, namely, Male, Female or Prefer not to say. The responses are presented in Figure 6 below.

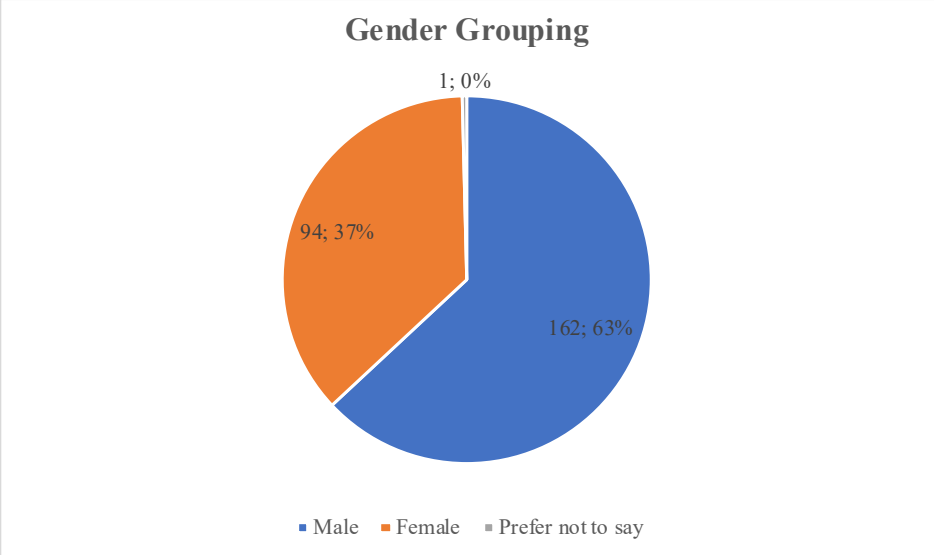

Figure 6: Gender Summary

Males made up the majority of the respondents at 63.04% (n = 162) while Females made up 36.58% (n = 94). There was a single participant that preferred not to classify themselves as either male or female 0.39% (n = 1). The large representation of males within this study is aligned with the findings that Information Technology departments are prominently male-based with an underrepresentation of females (Long, 2020).

4.3.3 Employer Name

Each participant was requested to indicate in which of the "Big Four" banks they work, Figure 7 provides a graphical representation of these results. FirstRand Bank (n = 148; 57%) makes up the largest portion of the data. This is potentially due to the fact that the researcher is currently employed with FNB for 10 years and has a large network of the potential sample population. The other three banks make up a similar portion of respondents with Nedbank (n = 38; 15%) being the second largest Bank. Standard Bank (n = 36; 14%) and ABSA (n = 35; 14%) make up the remaining portions of the respondents.

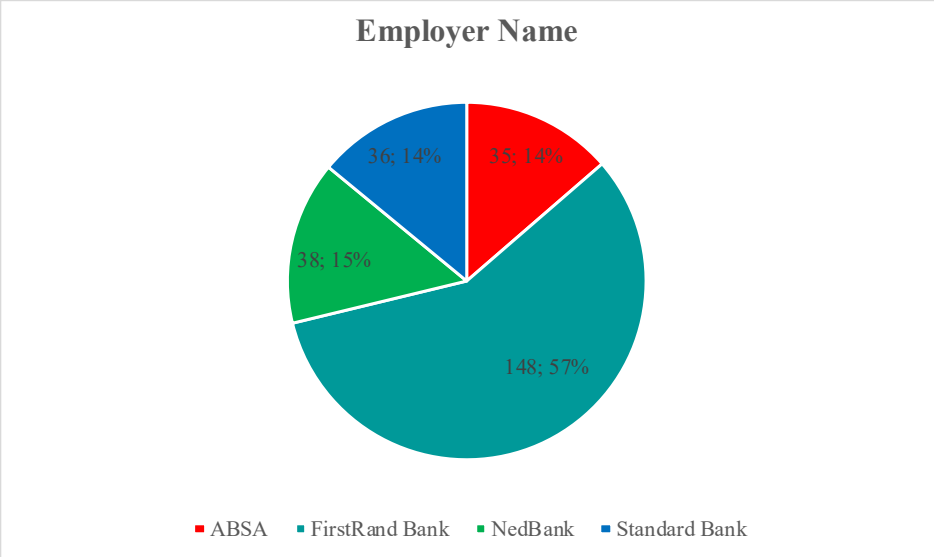

Figure 7: Employer Split

Gender	Employer Name				Total
	ABSA	FirstRand Bank	NedBank	Standard Bank	
Male	71,43%	59,46%	73,68%	58,33%	**63%**
Female	28,57%	40,54%	26,32%	38,89%	**37%**
Prefer not to say	0,00%	0,00%	0,00%	2,78%	**0%**
Grand Total	**100%**	**100%**	**100%**	**100%**	**100%**

Table 10: Employer Split vs Gender

An additional analysis was performed to compare the respondents Gender vs their Employer's Name, these groupings are displayed as a cross-tabulation in Table 10. FirstRand Bank and Standard Bank had a somewhat even distribution of Male and Female respondents at (m = 59.46%; f = 40.54% and m = 58.33%; f = 38.89%). This shows that even though FirstRand Bank makes up the majority share of the respondents, an even representation of genders was also present. ABSA and Nedbank both had similar distributions skewing more towards the Male respondents at (m = 71.43%; f = 28.57% and m = 73.68%; f = 26.32%).

4.3.4 Education Level

Figure 8 demonstrates that the bulk of the respondents have furthered their studies with a Post Graduate degree or greater at (n = 131) with respondents with a Bachelor's degree making up the second largest group at (n = 86). The remaining respondents reported having either a National Diploma (n = 23) or a Matric Certificate (n = 17). Interestingly 84% of all participants indicate that they hold a Bachelor's degree or higher (n = 217; 84%) which indicates that there is an expectation to have furthered our studies in order to be an employer within the "Big Four" banks (Haripersad, 2023)

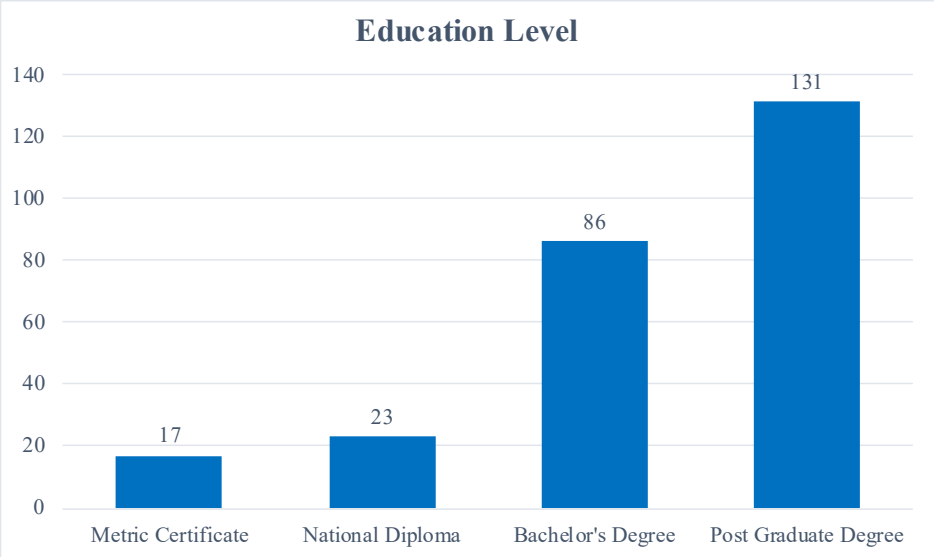

Figure 8: Education Levels

Table 11 represents a cross-tabulation of the Employer Names and the respondent's Education levels. Similar results can be observed across all four employers with ABSA not having a single respondent that at a minimum has a Matric Certificate (0%) while Standard Bank on the other hand had the largest percentage of respondents who only had a Matric Certificate (11.11%).

Education Level	Employer Name				Total
	ABSA	FirstRand Bank	NedBank	Standard Bank	
Matric Certificate	0,00%	7,43%	5,26%	11,11%	**7%**
National Diploma	5,71%	9,46%	5,26%	13,89%	**9%**
Bachelor's Degree	31,43%	33,11%	39,47%	30,56%	**33%**
Post Graduate Degree	62,86%	50,00%	50,00%	44,44%	**51%**
Total	**100%**	**100%**	**100%**	**100%**	**100%**

Table 11: Employer Split vs Education Level

4.3.5 Employment Level

A fairly even distribution is observed in terms of the employment levels as indicated by the respondents in Figure 9. Middle Management (n = 106) made up the largest population of the sample while Lower-level Management (n = 63) made up the second largest group of respondents. Upper Management (n = 47) and Consultants (n = 41) remaining respondents.

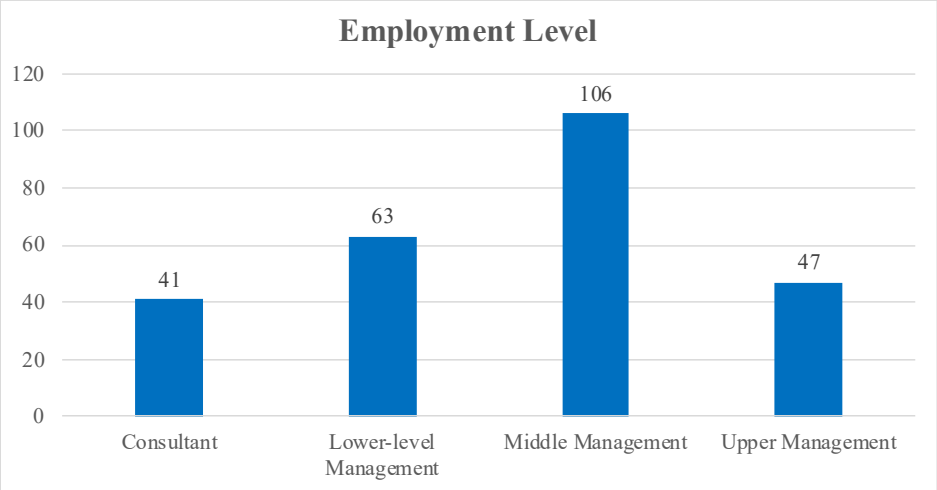

Figure 9: Employment Level

Based on the results presented in Table 12, most of the Upper Management respondents come from ABSA and Standard Bank at (31.43% and 38.89%). The rest of the distributions (Consultants, Lower-level Management and Middle Management) are in line with one another across the four banks with FirstRand Bank and Nedbank once again displaying similar distributions across the various categories.

Employment Level	Employer Name				Total
	ABSA	FirstRand Bank	NedBank	Standard Bank	
Consultant	11,43%	16,89%	21,05%	11,11%	**16%**
Lower-level Management	17,14%	27,70%	26,32%	16,67%	**25%**
Middle Management	40,00%	43,24%	42,11%	33,33%	**41%**
Upper Management	31,43%	12,16%	10,53%	38,89%	**18%**
Total	**100%**	**100%**	**100%**	**100%**	**100%**

Table 12: Employer Split vs Employment Level

4.3.6 Does the respondent work within a Business Intelligence Department?

Figure 10 depicts the split of the employees working within a BI department to those that do not work within the BI department.

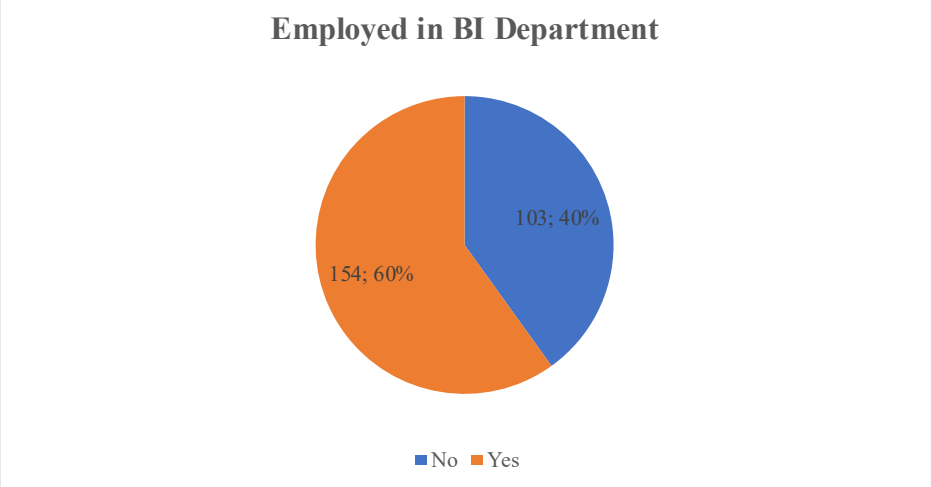

Figure 10: Employed in BI Department

The results indicate that 60% (n = 154) of the respondents work within a business intelligence department with the remaining 40% (n = 103) indicating that they do not. This result is understandable as the majority of the researcher's LinkedIn follower base is employed within the Data and Analytics field. This split, however, provides the researcher with an opportunity to understand the phenomenon from two viewpoints, one from within the BI department as the creators of the reporting models and another from the consumers and decision makers who consume the reporting models.

4.3.7 Have you heard of Self-Service Business Intelligence before this study?

Based on Figure 11 below, a significant portion of the respondents has heard of self-service business intelligence before at 85% (n = 219) while the remaining 15% (n = 38) respondents have indicated that they have never heard of the self-service business intelligence methodology before this survey.

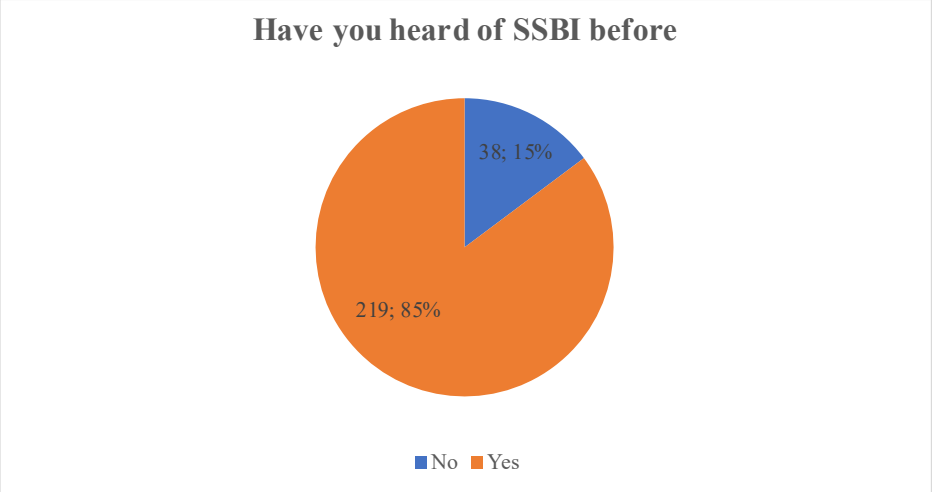

Figure 11: Have you heard of SSBI before this study?

4.3.8 How often do you make use of Self-Service Business Intelligence?

When asked how often each of the respondents makes use of self-service business intelligence, we also need to be cognizant of the large portion (85% as represented in Figure 10) of the sample population which works within a BI department. The respondents were asked to indicate how often they make use of SSBI reporting models based on the scale of (Never, Daily, Weekly or Monthly). These results have been presented in a stacked bar chart shown in Figure 12. The chart has been designed to illustrate the split between the respondents working within a BI department and those who are not, indicated by the "Yes and No" groupings while also overlaying the rating scale of how often they make use of SSBI.

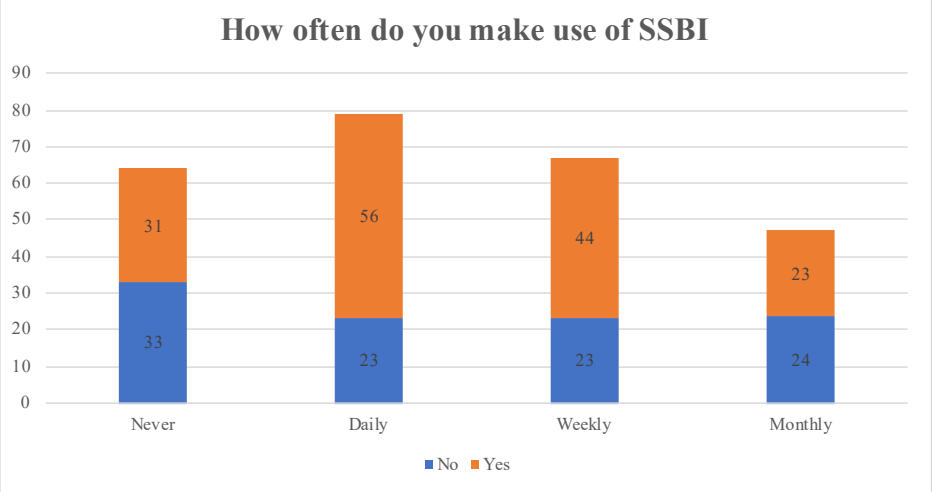

Figure 12: How often do you make use of SSBI reports?

The total respondents which have indicated that they never make use of SSBI (n = 64) have an even split between those working within a BI department (n = 31) and those who do not (n = 33). Respondents that indicated daily usage of SSBI (n = 79) swayed mostly towards the BI employees (n = 56) while the non-BI employees made up the remaining (n = 23). Weekly users (n = 67) saw a similar split between the BI employees (n = 44) and (n = 23) for the non-BI employees. Lastly, the respondents who indicated that they only make use of SSBI on a monthly basis (n = 47) once again showed a similar split between the BI and non-BI employees (n = 23) and (n = 24) respectively.

We are able to observe that out of all the BI employees (n = 154), 20% do not make use of SSBI at any stage of their monthly tasks. While only 32% of the non-BI employees (n = 103) never make use of SSBI. This statistic could be viewed as an indication of how well the banks are implementing their SSBI methodology, however, we still noticed that just under a quarter of the sample population have never made use of SSBI even though the reporting methodology has started to be implemented into their environments, further demonstrating the need research on the adoption of SSBI within the banking sector of South Africa.

4.3.9 Demographic Analysis Summary

In summation, the demographic statistics discussed above indicate that the majority of the sample population identifies as male (n = 162; 63%), aged between 31 and 40 (n = 124; 48%). More than half 51% (n = 131) of the respondents have furthered their studies with a post-graduate degree which is understandable as the focus of the study is related to individuals who are creators or consumers of business information for a decision-making process. 41% (n = 106) of the respondents are employed within a middle management level of the Banks. The bulk of the respondents (n = 219; 85%) indicated that they have at some stage heard of the SSBI methodology before completing the online survey with 75% (n = 193) of these respondents indicating that they make use of SSBI reporting models during the month.

A key observation noted during these statistical analyses indicates that although 75% of respondents make use of SSBI, the majority of these respondents indicated that they work within a BI department. 32% of non-BI employees have indicated that they have never made use of any SSBI reporting models. This suggests that either the SSBI reporting methodology is in an infant state within the banking industry, where only the BI users are able to view and make use of the models at present. Or it suggests that the adoption of SSBI is lacking within the banking industry, especially from the decision-maker's point of view.

4.4 Reliability Testing

The next stage of the analysis process was to conduct a reliability test on the various constructs within the research framework. This test is performed to determine the reliability of each construct in order to ensure that they are both dependable and consistent within the research (Bhattacherjee, 2012; Hair et al., 2010).

Constructs	Reliability Statistics		
	Cronbach's Alpha	No of Items Measured	Reliability
Job Fit (JF)	0,874	6	Good
Complexity (CP)	0,833	7	Good
Affect Towards Use (ATU)	0,755	7	Acceptable
Social Factors (SF)	0,849	4	Good
Long-Term Consequences (LTC)	0,878	4	Good

Facilitating Conditions (FC)	0,871	6	Good

Table 13: Reliability Test Results

As indicated in Table 5 a Cronbach Alpha result of 0.70 or higher is generally considered an acceptable result while a score of 0.60 may be used within exploratory research due to the theory formulation (Gliem & Gliem, 2003; Hair et al., 2010). Table 13 above provides the Cronbach's Alpha results for each construct within the model. The construct Affect Towards Use (ATU) produced the lowest alpha score (α = 0.755), however, this score is still well within the acceptable range. The remaining five constructs Job Fit (JF), Complexity (CP), Social Factors (SF), Long-Term Consequences (LTC) and Facilitating Conditions (FC) all produced results over (α > 0.8) indicating that their reliability is of a good standard. These scores indicate that the constructs are reliable and can be utilised within the subsequent analyses.

4.5 Factor Analysis

The purpose of conducting a factors analysis according to Hair et al., (2010), is to produce a defined structure, that is based on the variables within the analysis. This means that a large set of variables can be reduced and the variables which are grouped together during the factor analysis share some sort of relationship. This process will assist the research in determining the relationships within the variables and can be used to further explain the regression analysis to that will be conducted.

Before conducting a factor analysis on the data collected within the research, a few statistical tests needed to be conducted to ensure that the sample size collected is adequate for testing the phenomenon. The first of these tests was the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (Halim & Ishak, 2014; Pechenizkiy et al., 2004).

Kaiser-Meyer-Olkin Measure of Sampling Adequacy		.909
Barlett's Test of Sphericity	Approx. Chi-Square	4857.474
	df	406
	Sig.	.000

Table 14: KMO and Bartlett's Test

When deciding whether to proceed with the Principle Component Analysis (PCA), it is recommended that the KMO score is above 0.50. The results presented in Table 14 depict the KMO and Barlett's test results achieved from the research dataset. A KMO score of 0.909 was achieved which is excellent when compared to the KMO acceptance levels presented in Table 6. The significant value calculated in the Barlett's test of Sphericity achieved (p = 0.000), which indicated a significant result. By observing the results of both statistical tests, a conclusion was drawn that the sample size collected is satisfactory and that there are variables which are inter-correlated, therefore, the data is suitable to conduct a factor analysis.

A preliminary factor analysis was conducted on the data and it was identified that a total of five variables should be excluded from the final factor loading due to the fact that either their coefficient score was less than the absolute

value of 0.50 or they were loading across multiple factors (Halim & Ishak, 2014). The eventual PCA analysis was conducted with the use of varimax rotation on the remaining 29 variables, from which six distinctive factors were identified based on their eigenvalues being greater than one which accounted for 69.24% of the accumulative variances as shown in Table 15 below (Hair et al., 2010).

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	10.245	35.328	35.328	10.245	35.328	35.328	5.257	18.126	18.126
2	4.072	14.042	49.370	4.072	14.042	49.370	3.902	13.454	31.580
3	1.994	6.877	56.247	1.994	6.877	56.247	3.342	11.523	43.102
4	1.471	5.073	61.320	1.471	5.073	61.320	2.851	9.832	52.934
5	1.252	4.318	65.638	1.252	4.318	65.638	2.797	9.643	62.577
6	1.044	3.601	69.239	1.044	3.601	69.239	1.932	6.662	69.239
7	.926	3.195	72.434						
8	.756	2.607	75.041						
9	.658	2.269	77.310						
10	.571	1.970	79.280						
11	.550	1.897	81.178						
12	.521	1.797	82.975						
13	.504	1.736	84.711						
14	.433	1.492	86.204						
15	.415	1.432	87.636						
16	.390	1.346	88.981						
17	.365	1.258	90.239						
18	.345	1.189	91.428						
19	.317	1.095	92.523						
20	.306	1.056	93.579						
21	.273	.942	94.520						
22	.260	.895	95.415						
23	.244	.843	96.258						
24	.237	.817	97.075						
25	.221	.761	97.836						
26	.193	.667	98.503						
27	.177	.609	99.112						
28	.156	.539	99.652						
29	.101	.348	100.000						

Extraction Method: Principal Component Analysis.

Table 15: Total Variance Explained

The six factors and their respective loadings that influence the adoption of self-service business intelligence (SSBI) are presented in Table 16 below. Each of the factors was sorted by the highest to lowest coefficient values, indicating the level of influence each variable had on the overall factor loaded (Baah et al., 2015; Hair et al., 2010; Halim & Ishak, 2014). Each factor will be briefly discussed below.

4.5.1 Factor 1: Long-term Consequences

Factor 1 relates to the long-term consequences of adopting SSBI within the Banking sector of South Africa. It is indicated as the most important of the six factors equating to 35% of the total variance. Based on the results the respondents believe that the adoption of SSBI will have a positive impact on the bank, indicated by the highest coefficient loading of ($\beta = 0.816$). Closely followed as the second and third highest loading at ($\beta = 0.799$ and $\beta = 0.798$) respectively indicating that SSBI will save costs for the bank while agreeing that the shift towards the adoption of SSBI is the correct decision. A theme of improvement in productivity can be seen in the loadings for the fourth and fifth loadings at ($\beta = 0.778$ and $\beta = 0.754$).

4.5.2 Factor 2: Complexity

Moving on to the second factor which relates to the complexity of the adoption of the SSBI reporting dashboards within the banks adding an additional 14.04% to the total variance. The variables indicating that the dashboards are too complicated to understand and navigate loaded particularly close to one another at (β= 0.796 and β= 0.795) indicating that the respondents believe that these two concepts are linked and that their level of understanding of the dashboards is impacted by their ability to navigate them. The remaining three variables loaded in the factor indicate a similar theme with all the variables loading above 0.7.

4.5.3 Factor 3: Facilitating Conditions

Additionally, factor three added an additional 6.88% to the total variance and refers to the facilitating conditions when adopting SSBI within the banks. The respondents have identified that, the presentation of the information within the SSBI dashboards and how this information is formatted before being presented as the two highest loading variables at ($\beta = 0.770$ and $\beta = 0.738$) respectively. Further to that, the overall design of the SSBI dashboards and the respondent's ability to extract the required information loaded closely as a theme within the factor at ($\beta = 0.705$, $\beta = 0.700$ and $\beta = 0.698$).

4.5.4 Factor 4: Social Factors

Factor four added an additional 5.07% to the total variance and relates to the social factors affecting the adoption of SSBI within the banks. The BI department's willingness to assist and train the various business users on how to effectively make use of the SSBI dashboards loaded as the two highest social factors at ($\beta = 0.813$ and $\beta = 0.806$). The encouragement to adopt SSBI from the Bank as well as the respondents' managers also indicated an importance loading at ($\beta = 0.754$ and $\beta = 0.725$) respectively.

4.5.5 Factor 5: Job Fit

Furthermore, factor five referred to the job fit and added an additional 4.32% to the total variance. The need for SSBI dashboards to complete business tasks is evident in its loading of ($\beta = 0.751$) while the usefulness of the dashboards in completing business tasks also loaded high at ($\beta = 0.719$). The respondents indicated that the improvement which the SSBI dashboards might have on their business tasks has relative importance loading at ($\beta = 0.686$).

4.5.6 Factor 6: Affect Towards Use

Lastly, the sixth factor addresses the affect towards use by adding an additional 3.6% to the total variance. The respondents indicated that there is a high level of apprehension when making use of the data extracted from the SSBI dashboards by themselves loading at ($\beta = 0.815$). Feelings of anxiety when making use of the dashboards loaded as the second highest loading at ($\beta = 0.683$) while feelings of dislike to the additional work required in order to obtain the required information from the dashboards was the last loading of ($\beta = 0.641$).

Component	1	2	3	4	5	6
SSBI will change the Bank for the better.	.816					
Adopting SSBI can potentially save costs for both my department and for the Bank.	.799					
I agree with a shift towards a SSBI working methodology.	.798					
I believe that by making use of SSBI Dashboards, I will be able to improve my productivity.	.778					
Adopting SSBI Dashboards will give me the confidence to look for other opportunities to improve my productivity.	.754					
The fact that the SSBI Dashboards are online and available at anytime is important to me.	.670					
Making use of SSBI Dashboards will decrease the time required to make decisions within my role.	.575					
I enjoy the freedom which the SSBI Dashboards give me within my role.	.521					
The SSBI Dashboards are too complicated to understand.		.796				
The SSBI Dashboards are too complex to navigate.		.795				
I find it difficult to extract the required information from the SSBI Dashboards.		.741				
I am not able to achieve my desired results while working on the SSBI Dashboards.		.730				
I find it difficult to locate the appropriate SSBI Dashboard for the particular information I require.		.725				
The flow of the information within the SSBI Dashboards is simple to understand and follow.			.770			
The information in the SSBI Dashboards is formatted in such a way that it makes my job easier.			.738			
The SSBI Dashboard designs are intuitive and easy to navigate and understand.			.705			
The SSBI Dashboards are structured in such a way that I am able to extract the information needed.			.700			
I am able to extract information at varying levels of detail from the SSBI Dashboards.			.698			
The BI department is willing to assist me in understanding the SSBI Dashboards.				.813		
The BI department is willing to train me on the functionality of the various SSBI Dashboards.				.806		
My work place encourages me to make use of SSBI Dashboards.				.754		
My manager/supervisor encourages me to make use of the SSBI Dashboards.				.725		
There is a need for SSBI in order to complete my Daily/Weekly/Monthly reporting needs.					.751	
I find SSBI Dashboards useful for the managing of my Daily/Weekly/Monthly reporting needs.					.719	
I believe that SSBI can be used to improve my Daily/Weekly/Monthly reporting capabilities.					.686	
Being able to make use of the SSBI Dashboards in order to plan for future events is critical to the success of my role.					.600	
I feel apprehensive when I need to report from the information I extract from the SSBI Dashboards.						.815
I feel anxious when I need to make use of the SSBI Dashboards						.683
I dislike the fact that I need to do extra work to obtain my required information.						.641

Table 16: Rotated Component Matrix

4.6 Inferential Statistics

4.6.1 Introduction

Inferential analysis techniques, particularly multiple ordinal regression, were conducted to test the research question: *What influence does an individual's human factors have on their adoption of SSBI within the South African Banking Industry?*

In order to use the information collected within the online survey, composite variables were created by determining the average of each construct across all the responses. Producing composite variables is a method of reducing a large number of measures/items into grouped variables which represent both the independent and dependent variables being investigated within the research model (Bhattacherjee, 2012). A multiple regression technique was used in order to test the proposed hypothesis in section 2.12.7 above. Multiple regression is a method of statistical analysis in which the relationship between a dependent (outcome) variable can be predicted by multiple explanatory variables. Regression analysis is capable of calculating the magnitude that each explanatory variable has over the dependent variable (C. K. Chen & Hughes Jr, 2004; Field, 2009).

4.6.2 Descriptive Analysis

Composite variables were created for each of the independent variables (Job Fit, Complexity, Affect Towards Use, Long-Term Consequences, Social Factors, Facilitating Conditions) as well as the dependent variable (SSBI

Adoption) based on the mean scores of the various measures extracted from the online survey (Bhattacherjee, 2012; Song et al., 2013).

Statistic	N	Minimum	Maximum	Mean	Std. Deviation
Job Fit Avg	257	2,670	5,000	4,356	0,575
Complexity Avg	257	1,000	4,430	2,593	0,682
Affect Towards Use Avg	257	2,430	5,000	3,831	0,572
Social Factors Avg	257	1,000	5,000	3,895	0,813
Long-Term Consequences Avg	257	1,750	5,000	4,288	0,606
Facilitating Conditions Avg	257	2,170	5,000	4,009	0,632

Table 17: Composite Variable descriptive analysis

Table 17 represents the descriptive analysis for each of the newly created composite independent variables. Out of the six variables, Job Fit Avg has the highest mean score at ($\bar{X}$ = 4.356) indicating that the respondents exhibit the highest agreement that SSBI has the ability to improve their current work situation. From the Complexity Avg perspective, the respondents indicate primarily a negative response with a mean value of ($\bar{X}$ = 2.593) indicating that they find it difficult to navigate, view and extract the required information from the current SSBI reporting models. Affect Towards Use Avg and Social Factors Avg present similar somewhat positive results in their means of ($\bar{X}$ = 3.831 and $\bar{X}$ = 3.895) signifying that the respondents are experiencing encouragement from their respective Banks to make use of the SSBI reporting models while also indicating levels of apprehension while making use of self-extracted figures within reporting. Long-Term Consequences Avg presented the second highest mean score ($\bar{X}$ = 4.288) implying that the respondents see the potential benefits of adopting and making of SSBI over time which corresponds to Job Fit Avg being the highest variable. Facilitating Conditions Avg also indicates a positive response at ($\bar{X}$ = 4.009) signifying that the respondents agree that the reporting models have been set up in order to achieve the most efficient and effective reporting possible.

4.6.3 Distribution Analysis

Each of the composite variables were tested for normality in order to determine whether you are able to perform linear or ordinal regression can be conducted (C. K. Chen & Hughes Jr, 2004). A Kolmogorov-Smirnov and Shapiro-Wilk analysis was conducted on the composite variables as presented in Table 18 below. Normality is observed when the signification values are greater than the subsequent p-value identified for the particular level of confidence selected within the research as demonstrated in Table 19 below (Hair et al., 2010). It is generally accepted that for smaller sample sizes ($n \leq 50$), you would make use of Shapiro-Wilk, while for larger sample sizes, you may make use of Kolmogorov-Smirnov (Yap & Sim, 2011).

Construct	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Job Fit Avg	0,151	257	<0,001	0,904	257	<0,001
Complexity Avg	0,098	257	<0,001	0,981	257	0,001
Affect Towards Use Avg	0,073	257	0,002	0,984	257	0,006
Social Factors Avg	0,131	257	<0,001	0,943	257	<0,001
Long-Term Consequences Avg	0,154	257	<0,001	0,899	257	<0,001
Facilitating Conditions Avg	0,113	257	<0,001	0,959	257	<0,001

Table 18: Composite Variables test for normality

As presented in Table 18, each composite variable was tested for normality via both methods and obtained a significant value (p-Value) less than the significance value of 0.10, therefore, indicating that the variables are not normally distributed and as a result of this, ordinal regression was selected as the means to complete the hypothesis testing.

Level of Confidence	z Value	p Value (Sig.)
90% confidence	±1.65	< 0.10
95% confidence	±1.96	< 0.05
99% confidence	±2.57	< 0.01

Table 19: Confidence levels z values (Field, 2009; Saunders et al., 2009)

4.6.4 Correlation Analysis

As the results in section 4.6.3 have indicated that the data fails the test of normality, therefore, the Spearman's rank correlations will be utilised to infer the measures of association between the various constructs of the model (Hauke & Kossowski, 2011). Spearman's rank correlations Significance levels of the correlations are indicated as follows (*** is p-value < 0.001, ** p-value < 0.01, * is p-value < 0.05).

Construct Correlations								
Spearman's rho	Construct	Job Fit Avg	Complexity Avg	Affect Towards Use Avg	Social Factors Avg	Long-Term Consequences Avg	Facilitating Conditions Avg	SSBI Adoption Avg
	Job Fit Avg	1,000						
	Complexity Avg	-,283**	1,000					
	Affect Towards Use Avg	,448**	-,651**	1,000				
	Social Factors Avg	,406**	-,411**	,479**	1,000			
	Long-Term Consequences Avg	,670**	-,298**	,491**	,404**	1,000		
	Facilitating Conditions Avg	,508**	-,616**	,617**	,561**	,543**	1,000	
	SSBI Adoption Avg	,519**	-,537**	,648**	,597**	,573**	,769**	1,000

Table 20: Construct Correlation Analysis

Table 20 represents the results of the Spearman's correlation tests and has been compared to the correlations coefficient interpretations as presented by Schober & Schwarte, (2018) in Table 21 below. High significant relations between Facilitation Conditions (FC) and SSBI Adoption (AD) is visible through the strong correlation (ρ = 0.769**). Weak correlations were observed against Job Fit (JF) and Complexity (CP) as well as Long-Term Consequences (LTC) and Complexity at (ρ = -0.283** and ρ = -0.298**) respectively. The rest of the relationships all indicated a moderate correlation between the values of $\rho \geq 0.4$ and $\rho < 0.70$.

Correlation Coefficient	Interpretation
$\rho < 0.10$	Negligible correlation
$\rho < 0.40$	Weak correlation
$\rho < 0.70$	Moderate correlation
$\rho < 0.90$	Strong correlation
$\rho \geq 0.90$	Very Strong correlation

Table 21: Correlation interpretations(Schober & Schwarte, 2018)

4.6.5 Regression Analysis

Multiple regression analysis is a statistical technique where the probability of an outcome (dependent variable) is predicted based on the relationship data of a variety of different inputs (independent variables) (Bhattacherjee, 2012). As the data displayed a non-normal distribution as discussed in section 4.6.3 and due to the data collection process primarily making use of a Likert-scale to collect information relating to the phenomena, an ordinal regression analysis was an appropriate technique to be utilised for testing the hypothesis (C. K. Chen & Hughes Jr, 2004).

While conducting an ordinal regression analysis via SPSS, a variety of different outputs are produced which are used to determine how well the data fits into the proposed model and how well the model predicts the outcome variable (C. K. Chen & Hughes Jr, 2004; Field, 2009)

Model Fitting Information				
Model	**-2 Log Likelihood**	**Chi-Square**	**df**	**Sig.**
Intercept Only	1242,601			
Final	944,695	297,906	6	<0,001

Table 22: Model Fitting Information

The first important output produced by SPSS is the model fitting information as shown in Table 22. This information is used to reflect how well the model within the research fits the data. A significant result ($p < 0.10$) is required in order to prove that the model fits the data. Table 23 shows that the data fits the model well with a significant result of ($p < 0.001$). The second output to consider is the "Goodness-of-Fit" results, which is used to indicate whether the model is a good fit for the data being analysed. A non-significant result at $p > 0.10$ is required to prove "Goodness-of-Fit" (Field, 2009). The results of this test in Table 23 shows that the final model fits the data well by having a non-significant result.

Goodness-of-Fit			
	Chi-Square	**df**	**Sig.**
Pearson	2651,762	3550	1,000
Deviance	944,695	3550	1,000

Table 23: Goodness-of-fit

Pseudo R-Square	
Cox and Snell	0,686
Nagelkerke	0,692
McFadden	0,24

Table 24: Pseudo R Square

For ordinal regression, a Pseudo R-Square is used to represent the percentage of change in the dependent variable as a result of the independent variables within the model (Bhattacherjee, 2012; Field, 2009). Table 24 above indicates that a change of 69.2% (Nagelkerke $R^2 = 0.692$) in the dependent variable (SSBI Adoption) can be explained by the six independent variables included within the proposed model. The final test to consider is the test of parallel lines otherwise known as the test of proportional odds and is used to test for model adequacy by testing the odds of each independent variable being the same. A non-significant result at $p > 0.10$ is required for this test according to C. K. Chen & Hughes Jr, (2004). The results presented in Table 25 indicate that proportional odds are not significant (n = 0.915)

Test of Parallel Lines[a]				
Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	944,695			
General	883,194b	61,501c	78	0,915

Table 25: Test of Parallel Lines

Based on the above four statistical tests, it is clear that the model applied, and the data collected during the research fit well with one another, therefore, we are able to proceed with the hypothesis testing processes and procedures.

4.6.5.1 Hypothesis Testing Outcome

The results from the ordinal regression as provided in Table 26 below. The coefficient values represent whether the construct has any influence on the dependent variable (SSBI Adoption). As the research has been conducted at a 90% confidence level, a significant relationship between the independent and dependent variables requires a significations value ($p < 0.10$) as shown in Table 19 above.

Table of Coefficients									
Hypothsis #	Construct	Coefficients	Standard Error	Wald Statistic	df	Sig.	Lower 90%	Upper 90%	Outcome
H_1	Job Fit Avg	0.107	0.279	0.147	1	0.702	-0.352	0.565	Non-Significant
H_2	Complexity Avg	-0.004	0.241	0	1	0.987	-0.4	0.392	Non-Significant
H_3	Affect Towards Use Avg	0.887	0.312	8.065	1	0.005	0.373	1.401	Significant
H_4	Social Factors Avg	0.774	0.169	21.068	1	<0,001	0.497	1.051	Significant
H_5	Long-Term Consequences Avg	0.986	0.279	12.536	1	<0,001	0.528	1.444	Significant
H_6	Facilitating Conditions Avg	2.404	0.296	65.729	1	<0,001	1.916	2.891	Significant

Table 26: Table of Coefficients

By evaluating the p values of the coefficients for each of the respective independent variables in Table 26, we are able to test whether the hypothesis predicted in section 2.12.7 hold true or whether we will accept the null hypothesis.

$\boldsymbol{H_1}$**:** *Job fit has a significantly positive influence on the adoption of SSBI.*

Although we are able to see that Job Fit does has a positive influence on the adoption of SSBI indicated by the positive coefficient value of ($\beta = 0{,}107$). It was found to not be a significant predictor of SSBI adoption (p = 0.702) and therefore we reject the hypothesis and accept the null hypothesis stating that JF does not have a significantly positive influence on the adoption of SSBI.

$\boldsymbol{H_2}$**:** *Complexity has a significantly negative influence on the adoption of SSBI.*

Complexity was found to have a negative influence on the adoption of SSBI, however, it is not a significant predictor of the adoption of SSBI at values ($\beta = -0{,}004$; p = 0.987). In this event, we reject the hypothesis and accept the null hypothesis stating that CP does not have a significantly negative influence on the adoptions of SSBI.

$\boldsymbol{H_3}$**:** *Affect towards use will have a significantly positive influence on the adoption of SSBI.*

Affect towards use was found to have a significantly positive relationship on the adoption of SSBI confirmed by the outputs of ($\beta = 0{,}887$; p = 0.005). Therefore, we can accept the hypothesis that Affect Towards Use will have a significant and positive influence on the adoption of SSBI.

$\boldsymbol{H_4}$**:** *Social factors will have a significantly positive influence on the adoption of SSBI.*

Social factors were found to have a significantly positive relationship on the adoption of SSBI shown in the output values ($\beta = 0{,}774$; p = < 0.001) accepting the hypothesis that Social Factors have a significant and positive influence on the adoption of SSBI.

$\boldsymbol{H_5}$**:** *Long-term consequences will have a significantly positive influence on the adoption of SSBI.*

It was found that Long-term consequences has a significantly positive relationship on the adoption of SSBI confirmed by the outputs ($\beta = 0{,}986$; p = < 0.001). Therefore, accepting the hypothesis that Long-term will have a significant and positive influence on the adoption of SSBI.

$\boldsymbol{H_6}$**:** *Facilitating Conditions will have a significantly positive influence on the adoption of SSBI.*

Facilitating conditions was found to be a highly significant predictor of the adoption of SSBI ($\beta = 2{,}404$; p = < 0.001). Therefore, we can accept the hypothesis that states that Facilitating Conditions will have a significant and positive influence on the adoption of SSBI.

Chapter 5: Discussion, Recommendations and Limitations

5.1 Introduction

With the progressive value and importance of data, industries are realising that in order to succeed and progress they need to ensure that they are able to get the most out of their data. This is why the BI departments are needed. BI departments have been put together over the years with the primary goal of transforming data into usable information which can be used within the decision-making process, allowing the business to gain an advantage over its competitors (Ain et al., 2019; Caseiro & Coelho, 2019; Hartl et al., 2016; Immhoff & White, 2011; Sulaiman & Gómez, 2018).

The increase in the volume of data seen during the recent shift (Phase 3) in the BI environment has brought on new challenges that need to be considered by the BI departments. The implementation of new technologies and the impact of limited human capital has forced the BI departments to do more with less (Aljarba et al., 2019; Stjepić et al., 2021). This ideology impacts the BI department's ability to produce information timelessly in order for the business to make critical business decisions, subsequently driving the development and need of the SSBI methodology (Aljarba et al., 2019; Olszak, 2016; Owusu, 2017; Stjepić et al., 2021). SSBI came about to assist both the business and the BI departments with a more dynamic approach to generating and reporting on information (Maryska & Doucek, 2017). From a business aspect, the end users are able to obtain information in a manner which is faster than the traditional method. This is achieved through methods and tools which an end-user could make use of as and when they require. For the BI department, SSBI provides relief from the bottleneck of information requests while also allowing the BI analysts to focus on the creation of knowledge within the business. Instead of working on numerous reporting requests, the BI departments are able to focus on creating and enhancing the various data marts which feed the reporting models used by the business end-users.

As SSBI is able to benefit not only the BI departments but the business as a whole, research should be considered in order to determine how this methodology can best be successfully implemented and adopted within the business.

This research was conducted to examine the human factors that influence the adoption of SSBI within the banking sector of South Africa. Based on the literature review, it was identified that limited research has been conducted on the adoption of SSBI from a human factor aspect. This was particularly evident in investigating how these factors influence the adoption of SSBI (Jooste et al., 2018; Weiler et al., 2019). This statement was confirmed through a systematic literature review conducted by de Waal & Budree, (2022). It was identified in this research that the primary focus of the adoption research within the BI and SSBI field has been from an organisational stance, where the incorporation of the BI components within the business and its strategy(s) were observed through the use of the TOE and DOI frameworks. A recommendation of the review was to employ the theoretical framework Model of PC Utilisation (MPCU) while examining the adoption of SSBI within the banking sector of South Africa. The MPCU adoption framework has not been used in prior research to examine the adoption of BI let alone the adoption of SSBI, however, the MPCU framework shares similar traits to those of the other adoption frameworks (discussed in section 2.11 above) which have been used in prior research. Comparisons in the results observed within this research will be

inferred from prior research conducted on the topic that has made use of one of the other possible adoption frameworks. This may be performed due to the similarities within the constructs measured by the models in certain cases which will determine whether the findings are in line with prior research or whether new findings have been uncovered (Hussein & Abdelhamid, 2021; Koul & Eydgahi, 2017; Li, 2010; Taherdoost, 2018).

In order to answer the research question "*What influence does an individual's human factors have on their adoption of SSBI within the banking sector of South Africa?"* we will first examine the underlying sub-research questions from section 1.4.1.

5.1.1 SQ_1: What impact does the influence of a manager, colleague or business have on the adoption of SSBI?

The research found that the support of either a manager, colleague or of the business plays a significant impact in the adoption of SSBI. Two of the MPCU constructs were considered when answering this question, namely, Affect Towards Use (ATU) and Social Factors (SF). Based on the correlation results in Table 20, ATU and SF indicate a significant and moderate correlation with one another at (ρ = 0.479**). This result was expected as it aligns with the thought that employees who enjoy and favour the use of SSBI will encourage other employees to also utilise the tool becoming a sort of champion for the tools. Aljarba et al., (2019) reported a similar observation indicating that with regular training sessions, an increase in the use of SSBI was observed due to the skill and confidence levels increasing in the employees while making use of the tools. Results from the regression analysis indicate that both the ATU and SF have a significantly positive influence on the adoption of SSBI with results of ($\beta = 0{,}887$ and $\beta = 0{,}774$) as expected based on the literature review conducted in Chapter 2. Similar results in terms of the importance of social factors and colleague support were observed in a study conducted by Bargshady et al., (2015) where the study focused on the user's acceptance factors of mobile BI. In a study conducted by Kohnke et al., (2011) where it was also found that the managerial support of BI and its functions were a key factor in the acceptance of BI within the business.

It is important to note that no matter how well or how much the business, manager or colleagues promote the adoption of SSBI within the business, the key to its successful adoption is the user and their willingness to accept, learn and integrate the reporting dashboards into their daily tasks. In a study conducted by Ain et al., (2019), it was found that the users' motivation is a key driver in their willingness to accept and adopt the BI tools and methodology. A business should be willing to spend the time and effort to showcase to the various users the benefits of SSBI. While further demonstrating that by incorporating these tools and methodology into their daily lives, it could save them a tremendous amount of time in the decision-making process.

5.1.2 SQ_2: What effect does the structure of the SSBI reporting models have on an individual's adoption of SSBI?

Moving on to sub-question two, it is assumed that in order to adopt and successfully integrate the technology into an individual's daily work routine, it should be sufficiently designed with the user experiences in mind (Linden, 2021; Michalczyk et al., 2020; Popovič, 2017). The MPCU makes provision for this assumption with the Complexity

(CP) and Facilitating Conditions (FC) constructs. These constructs focus on the complexity of the reporting dashboard designs as well as the functionality within the reporting tool. The results observed during the regression analysis in Chapter 4 suggest that CP and FC are significantly correlated with one another (ρ = -0.616**). This negative correlation is understandable due to the fact that when an individual finds a system difficult to utilise, the user will generally shy away from using it all together. According to the research conducted by Rouhani et al., (2018), the adoption of BI is negatively affected by an overly complex system. This shows that even within a BI department, the business might struggle to adopt and utilise a complex reporting system. Kohnke et al., (2011) noted a similar result, stating that the complexity of the system is strongly related to the adoption of BI. These findings interestingly contradict the findings of this research which indicates that CP does not have a significant effect on the adoption of SSBI ($\beta = -0{,}004$; p = 0.987). This is not to say that the system and its "perceived" complexity does not play a role in the adoption of SSBI. The four banks included in this research are well established within the global market which illustrations their willingness to adapt and evolve. The fact that CP does not have a significant effect on the adoption could be an indication of the fact that BI is already well ingrained into the fabric of the banking processes and strategies. FC is found to have a highly significant impact on SSBI's adoption ($\beta = 2{,}404$; p = < 0.001). This result indicates that the participants highly rate the relative ease of use, which is gained through the SSBI methodology, including the location and design of the reporting models already in place within the divisions of the bank. According to Alpar & Schulz, (2016), research needs to be continuously conducted in order to determine the best possible data representation techniques and facilitating conditions to improve the adoption of BI. Implying that there will always be room for improvement and as newer technologies emerge, so too is the research to ensure the successful implementation within the businesses. The results of this research is confirmed by both Bargshady et al., (2015) and Hänel & Schulz, (2014), signifying that the design and functionality of the reporting models play a significant role in the adoption of the BI and SSBI.

Although the complexity of the reporting models is shown to have no significance on the adoption of SSBI based on this research, the fact that the SSBI reporting models are available online and in the formats required by the business has been revealed to be the largest factor in its adoption through the lens of the MPCU in the context of this research. This is an important finding and is something that should be strongly considered by the various BI departments while designing and developing their reporting models. Time should be spent within the business and the focus should be squarely on their requirements while discussing the functionality needed to ensure successful usage. This effort will ensure that the business feels a part of the development process and is able to see the fruits of its vision come to life, therefore, assisting in making the adoption process smoother.

5.1.3 SQ_3: How does an individual's job requirement(s) influence their adoption of SSBI?

Lastly, as we consider sub-question three, the research has found that the respondents are able to understand the long-term benefits of adopting SSBI within their work routines, however, they are currently not in a state where complete adoption of SSBI makes sense to their current work requirements. The two constructs, Job-Fit (JF) and Long-Term Consequences (LTC) as presented in the MPCU are used when answering this question. The constructs focus on how SSBI can be used to improve the user's daily/weekly or monthly work requirements, while also gauging whether the respondents can recognise the future benefits SSBI provide upon its adoption. JF and LTC have a moderately high correlation (ρ = 0.670**). This observation aligns with the assumption that when the employees realise the potential

future benefit(s) of changing their behaviour and adopting the new technology, the expected result would be that their current roles will be made easier. Based on the results of the regression analysis, JF is found to not be significant in the adoption of SSBI within this study (β=0,107; p = 0.702). This result indicates that the respondents currently are not able to realise the benefits of SSBI within their current job requirements, which could possibly be due to the current implementation phases of SSBI within the numerous divisions of the "Big Four" banks. A similar result is observed by Weiler et al., (2019) where the users indicate resistance to the adoption of SSBI due to the uncertainty of how SSBI can be incorporated into their daily/weekly/monthly tasks. Popovič, (2017) postulates that with the adoption of SSBI, users are expected to change their thought processes and develop a new skillset to achieve their required goals which creates angst among the employees ending in resisting the adoption of SSBI.

On the other hand, LTC is found to be a highly significant predictor of the adoption of SSBI within the MPCU (β=0,986; p = < 0.001). This result is evidence that the user can see the future benefits of adopting SBSI from both a personal as well as from the bank's point of view. This can be partly due to the results of the current constraints within the traditional BI methodology, where the end user is not able to make decisions timelessly as they have to wait for the BI departments to put together the required information before sending. Kohnke et al., (2011) found in their study that the adoption of SSBI is strongly related to the quality of the information presented in the reporting dashboards further implying that the user is able to see the benefits of adopting SSBI as long as strict attention to detail is considered when building the reporting models. Ain et al., (2019) confirmed this finding in their study, stating that users are more willing to adopt SSBI if they can trust the information presented as well as understand how the system functions for them to get the most out of it.

An important observation from these results illustrations that the benefits of SSBI are widely accepted within the banking industry. The respondents are aware that the methodology can benefit them in the long term, however, the main constraint is their willingness to learn a new skill that will initially add to their current daily/weekly or monthly workload. Emphasis on training the employees on the SSBI reporting models is key to its adoption. The training needs to be centred around the user's needs and not just a general overview. Once the user builds their confidence in the reporting model and understanding of how to navigate and extract the information, the angst of getting it wrong will subside and an uptick of usage should be seen.

5.2 Conclusion

The adoption of BI has been researched for many years with the focus primarily being on the adoption and integration of BI, its tools, and methodologies within an organisation. This research set out to examine whether an individual's human factors play a role in their ultimate adoption of SSBI. The MPCU framework was used to investigate this aim and it was found to explain 69.2% of the phenomena (based on the pseudo-R square value as shown in Table 24). This indicates that a large portion of the adoption of SSBI within the banking sector of South Africa relates to the various human factors of the individuals.

The research found that the integration of SSBI into the individual's current role as well as the complexity of the models were not significant driving factors in the adoption of SSBI but instead, factors relating to the individual's attitude and social influences played a greater role in its overall adoption. This finding, coupled with the finding that users are mindful of the future benefits that SSBI will provide them with indicates that we cannot overlook how human factors influence the adoption of SSBI. The humanistic point of view when it comes to the adoption of SSBI is significant and should be considered more by the BI departments. It is clear from the results that the method of distribution as well as how the reporting dashboards are formatted are significant factors for the individual's adoption of SSBI. These aspects should be keenly considered by the BI departments when designing and implementing the SSBI solutions within the business. This would in turn ensure that the business gets the most out of the SSBI reporting models. As new reporting models are developed, or new functionality is added to the reporting models, guidance and training should remain a key focus area of the BI departments. The aim of this training should be to build the users' confidence levels, not only in the tool(s) but also in their capabilities to extract accurate information from the SSBI reporting models.

5.3 Research Contribution

This study has contributed academically to the Information Systems field as well as industrially by highlighting areas which should be considered during the implementation of SSBI. There has been a need to investigate the human aspect that drives the adoption of SSBI (Weiler et al., 2019). This study contributes to help understanding this gap in the literature by making use of the Model of PC Utilisation framework that focuses on the human in the adoption process.

The literature review identified the bias in past research which focused mainly on the adoption from an enterprise stance as well as a systems design point of view (de Waal & Budree, 2022). This could mainly be due the current life cycle of the self-service nature of BI. Focus initially needs to be placed on integrating the SSBI systems into the enterprise. Additionally, the design and structures of the tool(s) need to be made user friendly to ensure uptake.

Practically, this research has contributed to the understanding that a large portion of the adoption of SSBI within the banking sector of South Africa can be attributed to humanistic factors. By making use of the Model of PC Utilisation, a fresh outlook of adoption is considered. This is not to say that a business should not be aware of how the reporting technology will be integrated into its current environment, systems and strategies. Rather, these findings should be incorporated with the humanistic factors which influence the adoption of SSBI to improve its overall adoption levels. A key contribution is confirming that adoption from a top-down approach in which users are influenced and guided by influential parties within the business is found to be the largest predictor of whether someone will adopt SSBI or not. Confirming the findings of Weiler et al., (2019) where it was indicated that social influences are an important aspect to consider in adoption.

Finally, this research should be considered as a base to further enhance our understanding of how various human aspects influence adoption. This should be done but enhancing and altering the MPCU framework to provide a more concise view of adoption from a humanistic point of view.

5.4 Limitations

As with any research, it is important to highlight the potential limitations observed during the research process.

This research made use of a quantitative research approach by employing an online questionnaire focused solely on the "Big Four" banks of South Africa. Assuming that these results could be extended to the other banks within South Africa, let alone the rest of Africa, this should be done with caution due to the established nature of the "Big Four" banks within both the industry as well as in their technological advancements. Future research should be considered across other developing countries to determine the generalizability of the findings from this research.

Over half of the sampled population were taken from FNB, again, this was possibly due to fact that the researcher works for FNB and the convenience of having access to more of the targeted populations within that bank. However, the other remaining 3 targeted banks were represented within the sampled population, and it is safe to claim that the research was not a pure assessment of FNB's adoption of SSBI.

Further to the type of research methodology employed, a potential for common method bias is present due to the collection of both the independent and dependent variables based on the MPCU framework within the same online survey. Although this is common practice within a quantitative study, this limitation should be considered when reviewing the relationships established between the independent variables and the adoption of SSBI.

The inclusion of both the consumers and producers of BI information within this research posed a partial participation bias limitation due to the inferences that can be drawn across the sampled populations. The producers of BI information have the additional advantage of knowing about and potentially making use of the SSBI methodology. While pure consumers of the BI information are merely subjected to what is presented to them in the formats allotted. Without adequate presentation, training and distribution of the SSBI reporting models, a pure consumer of BI information would find it difficult to make use of let alone adopt the SSBI methodology.

This research was conducted as a cross-sectional study which has its own limitations in terms of the time available to obtain responses from the sample population in order to conduct the statistics at a 95% confidence level. To overcome this limitation, the study was conducted at a 90% confidence level which was deemed to be sufficient for this research. Additional statistical tests were conducted on the data at a 95% confidence level and similar results were observed in all cases, proving that the 90% confidence level is sufficient within this research.

5.5 Recommendation for future research

Furthermore, in order to continuously enhance our understanding of the topic relating to the adoption of SSBI, it is important to consider the "what next" question. These question(s) or suggestions should be formulated based on the research, its limitations and how best they can be overcome for future research. The focus of this research was only on the "Big Four" banks of South Africa which are well-established within the industry. It is recommended to expand this research by exploring the newer banks within the industry to determine whether the established nature of the banks is

either an advantage or disadvantage in the adoption of SSBI due to their rigid structures, processes and systems that are in place. Further research should be conducted where the focus is squarely on the decision-makers who consume the SSBI reporting models. The researcher should consider making use of qualitative research techniques which afford an in-depth exploration based on the user's knowledge and experience of the phenomena.

Further exploratory research should be considered in order to expand and modify the MPCU framework by adjusting the inclusion variables in an attempt to increase the total variance which could be explained by the MPCU framework. Researchers should consider various variables such as age, education, employment levels and other human factors that could prove to enhance the total variance achieved by MPCU framework, therefore providing a deeper understanding of the phenomena which can be used to guide businesses that are in the process of implementing an SSBI methodology.

As this research was focused on the South African banking industry, it is further recommended to expand the research into other developing countries further developing the body of knowledge while also determining whether the impact of human factors plays any significance in the adoption of SSBI within these countries. Amendments to the research's inclusion criteria as well as alterations to the MPCU framework could be considered to further enhance the understanding of the impact that human factors have in the adoption of SSBI.

Business intelligence is not exclusively relevant to the banking sector. Sectors such as Insurance, Automotive and Healthcare all have key interests in their data and information. This information can be used to make critical decisions about their clients, possible sale opportunities, risks, and growth capabilities, to name a few, much like that within the banking sector. Opportunities exist for future research to expand into these business sectors in order to determine whether human factors play a role in their SSBI adoption life cycle, broadening the body of knowledge on the topic of adoption and SSBI while observing it from more than one sector.

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Appendices

Appendix A – Ethics Approval

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2.26 Leslie Commerce Building, Upper Campus
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Internet: www.uct.ac.za
@Commerce UCT **UCT Commerce Faculty Office**

15 02 2022

Sean de Waal

Department of Information Systems

University of Cape Town

REF: REC 2022/02/015

Examining the human factors that influence the adoption of Self-Service Business Intelligence within the banking sector of South Africa

We are pleased to inform you that your ethics application has been approved. Unless otherwise specified this ethical clearance is valid until 31-Dec-2023 .

Your clearance may be renewed upon application.

Please be aware that you need to notify the Ethics Committee immediately should any aspect of your study regarding the engagement with participants as approved in this application, change. This may include aspects such as changes to the research design, questionnaires, or choice of participants.

The ongoing ethical conduct throughout the duration of the study remains the responsibility of the principal investigator.

We wish you well for your research.

2022.02.15
21:56:11 +02'00'

Jacques Rousseau
Commerce Research Ethics Chair
University of Cape Town
Commerce Faculty Office
Room 2.26 | Leslie Commerce Building

Office Telephone: +27 (0)21 650 2695 / 4375
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Website: http://www.commerce.uct.ac.za/com/Ethics-in-Research

"Our Mission is to be an outstanding teaching and research university, educating for life and addressing the challenges facing our society."

Appendix B – Consent form

Department of Information Systems
Leslie Commerce Building
Engineering Mall, Upper Campus
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Private Bag X3 - Rondebosch - 7701
Tel: +27 (0) 21 650 2261 Fax: +27 (0) 21650 2280
Internet: http://www.commerce.uct.ac.za/informationsystems/

Examining the human factors that influence the adoption of Self-Service Business Intelligence within the banking sector of South Africa

Request to conduct research and interview participation consent form:

Dear Sir/Madam,

In terms of the requirements for completing a Master of Commerce Degree in Information Systems at the University of Cape Town a research study is required.

The researcher, in this case Sean de Waal, has chosen to conduct a study entitled "Examining the human factors that influence the adoption of Self-Service Business Intelligence within the banking sector of South Africa". The objective of the research is to examine the extent to which the various human factors impact the adoption of a Self-Service Business Intelligence methodology within the banking sector of South Africa.

You are invited to partake in an anonymous questionnaire. Your participation in this research is voluntary. All information will be treated in a confidential manner and used exclusively for the purpose of this study. No individual names or personal details will be recorded or published. You will not be requested to supply any identifiable information, ensuring the anonymity of your responses throughout the questionnaire.

By participating within this research, you are subsequently giving consent for the researcher to analyse your answers. You may choose to withdraw from the research at any time for whatever reason, in accordance with ethical research requirements. The findings of this research will be compiled into a report and presented to the University of Cape Town for academic purposes.

The data collection method will make use of a questionnaire. The questionnaire will be conducted online via Google Forms and will require approximately 10 - 15 minutes to complete.

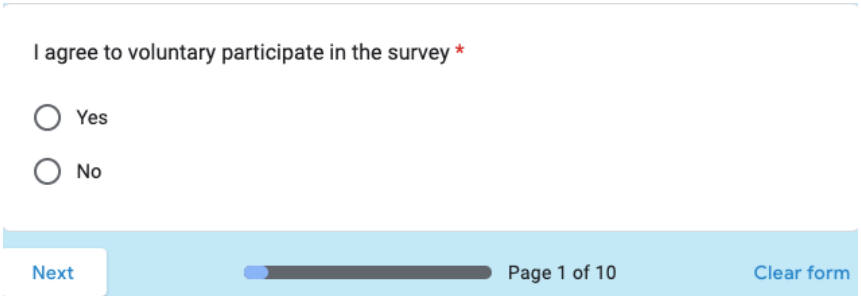
This research has been approved by the Commerce Faculty Ethics in Research Committee (REF: REC 2022/02/015). Should you have any questions regarding this research, please feel free to contact me on 084 240 6019 or email: DWLSEA001@myuct.ac.za

Your participation in this study would be greatly appreciated but is entirely voluntary.

Sincerely,

Sean de Waal
Researcher \ M.Com Student, (UCT)
Department of Information Systems
University of Cape Town
Email: DWLSEA001@myuct.ac.za

Adheesh Budree
Research Supervisor
Department of Information Systems
University of Cape Town
Email: adheesh.budree@uct.ac.za


I agree to voluntary participate in the survey *
Yes
No
Next
Page 1 of 10
Clear form

Appendix C – Questionnaire

Questionnaire

Section 1: Demographics

Section 1 relates to the general Demographics of the participant as well as their understanding of the research topic. Please select the option which best describes you as a participant.

Questions	Options	
1. Indicate your Age group:		18 – 25
		26 – 30
		31 – 35
		36 – 40
		41 – 45
		46 – 50
		> 50
2. Select your Gender:		Male
		Female
		Prefer not to say
3. What is your Highest level of Education?		No Qualification
		Matric Certificate
		National Diploma
		Bachelor's Degree
		Post Graduate Degree
4. Which Bank do you work for?		ABSA
		FirstRand Bank
		Nedbank
		Standard Bank
		Other
5. Indicate the option which best describes your position within the Bank.		Consultant
		Lower-Level Management
		Middle Management
		Upper Management
6. Do you work in a Business Intelligence department?		Yes
		No
7. Have you heard of Self-Service Business Intelligence?		Yes
		No
8. Do you make use of Self-Service Business Intelligence?		Yes
		No
9. How often do you make use of Self-Service Business Intelligence?		Never
		Daily
		Weekly
		Monthly
10. Do you see the potential benefit of Self-Service Business Intelligence within the Banking Sector?		Yes
		No

Section 2: Job Fit

Job-Fit refers to the extent to which Self-Service Business Intelligence will improve your ability to perform your current role. Kindly indicate to which extent you agree or disagree with the following statements:

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I believe that Self-Service Business Intelligence can be used to improve my Daily/Weekly/Monthly reporting capabilities.	1	2	3	4	5
There is a need for Self-Service Business Intelligence in order to complete my Daily/Weekly/Monthly reporting needs.	1	2	3	4	5
Making use of Self-Service Business Intelligence Dashboards will decrease the time required to make decisions within my role.	1	2	3	4	5
Making use of Self-Service Business Intelligence Dashboards will improve the quality of the decisions I make within my role.	1	2	3	4	5
Being able to make use of the Self-Service Business Intelligence Dashboards in order to plan for future events is critical to the success of my role.	1	2	3	4	5
I find Self-Service Business Intelligence useful for managing my Daily/Weekly/Monthly reporting needs.	1	2	3	4	5

Section 3: Complexity

Complexity refers to how difficult you as a user find the Self-Service Business Intelligence Dashboards in order to obtain the required information. Kindly indicate to which extent you agree or disagree with the following statements.

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The Self-Service Business Intelligence Dashboards are too complex to navigate.	1	2	3	4	5
The Self-Service Business Intelligence Dashboards are too complicated to understand.	1	2	3	4	5
I find it difficult to locate the apporpriate Self-Service Business Intelligence Dashboard for the particular infomrmation I require.	1	2	3	4	5
I find it difficult to extract the required information from the Self-Service Business Intelligence Dashboards.	1	2	3	4	5
I am not able to achieve the desired results while working on the Self-Service Business Intelligence Dashboards.	1	2	3	4	5
I find it easier to extract the raw data and design my own reports on tools like Microsoft Excel.	1	2	3	4	5
Learning how to make use of the Self-Service Business Intelligence Dashboards was easy for me.	1	2	3	4	5

Section 4: Affect towards Use

Affect towards use can be defined as the feelings (either positive or negative) that you experience while making use of the Self-Service Business Intelligence Dashboards. Kindly indicate to which extent you agree or disagree with the following statements.

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I am confident in my ability to extract the required information from the Self-Service Business Intelligence Dashboards.	1	2	3	4	5
I enjoy the freedom which the Self-Service Business Intelligence Dashboards give me within my role.	1	2	3	4	5
I dislike the fact that I need to do extra work to obtain my required information.	1	2	3	4	5
I feel anxious when I need to make use of the Self-Service Business Intelligence Dashboards	1	2	3	4	5
I feel apprehensive when I need to report from the information I extract from the Self-Service Business Intelligence Dasboards.	1	2	3	4	5
I get a sense of accomplishment when I have made use the Self-Service Business Intelligence Dashboards.	1	2	3	4	5
I agree with a shift towards a Self-Service Business Intelligence working methodology.	1	2	3	4	5

Section 5: Social Factors

Social factors relate to the degree of influence others will have on you in order to adopt the use of the Self-Service Business Intelligence Dashboards. Kindly indicate to which extent you agree or disagree with the following statements.

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
My work place encourages me to make use of Self-Service Business Intelligence Dashboards.	1	2	3	4	5
My manager/supervisor encourages me to make use of the Self-Service Business Intelligence Dasbhoards.	1	2	3	4	5
The Business Intelligence department is willing to assist me in understanding the Self-Service Business Intelligence Dashboards.	1	2	3	4	5
The Business Intelligence department is willing to train me on the functionality of the various Self-Service Business Intelligence Dashboards.	1	2	3	4	5

Section 6: Long-Term Consequences

The Long-term consequences refer to the future benefit(s) which you might observe by adopting the Self-Service Business Intelligence Dashboards. Kindly indicate to which extent you agree or disagree with the following statements.

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I believe that by making use of Self-Service Business Intelligence Dashboards, I will be able to improve my productivity.	1	2	3	4	5
Adopting Self-Service Business Intelligence will give me the confidence to look for other opportunities to improve my productivity.	1	2	3	4	5
Adopting Self-Service Business Intelligence can potentially save costs for both my department and for the Bank	1	2	3	4	5
Self-Service Business Intelligence will change the Bank for the better.	1	2	3	4	5

Section 7: Facilitating Conditions

Facilitating conditions refer to the degree with which the Self-Service Business Intelligence Dashboards are built in order assist you as the user to successfully complete your task(s). Kindly indicate to which extent you agree or disagree with the following statements.

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
The fact that the Self-Service Business Intelligence Dashboards are online and available at anytime is important to me.	1	2	3	4	5
The Self-Service Business Intelligence Dashboard designs are intuitive and easy to navigate and understand.	1	2	3	4	5
The Self-Service Business Intelligence Dashboards are structured in such a way that I am able to extract the information needed.	1	2	3	4	5
The information in the Self-Service Business Intelligence Dashboards is formated in such a way that it makes my job easier.	1	2	3	4	5
The flow of the information within the Self-Service Business Intelligence Dashboards is simple to understand and follow.	1	2	3	4	5
I am able to extract information at varying levels of detail from the Self-Service Business Intelligence Dashboards.	1	2	3	4	5

Section 8: Adoption of Self-Service Business Intelligence

Kindly indicate to which extent you agree or disagree with the following statements regarding the adoption of Self-Service Business Intelligence within your current role.

Question	Strongly Disagree	Disagree	Neither Agree nor Disagree	Agree	Strongly Agree
I am confident in the adoption and subsequent use of Self-Service Business Intelligence within my role.	1	2	3	4	5
I recommend the use of the Self-Service Business Intelligence Dashboards to my fellow colleagues.	1	2	3	4	5
I am willing to extract all the information I need from the Self-Service Business Intelligence Dashboards myself.	1	2	3	4	5
I proactively seek for opportunities in which I can extract information on my own using the Self-Service Business Intelligence Dashboards.	1	2	3	4	5
I do not require the assistance from the Business Intelligence department to extract information anymore.	1	2	3	4	5

Appendix D – Turnitin Results

turnitin

Digital Receipt

This receipt acknowledges that Turnitin received your paper. Below you will find the receipt information regarding your submission.

The first page of your submissions is displayed below.

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