

The impact of big data analytics capabilities on service innovation in state-owned enterprises: The moderating role of institutional pressure.

**Nature of study: Quantitative mono
study**

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in partial fulfilment of the requirements for the degree of Master of Business Administration.

4 November 2024

Declaration

I hereby declare that this research project titled 'The impact of big data analytics capabilities on service innovation in state-owned enterprises: The moderating role of institutional pressure', submitted for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria, is my original work and has not been submitted previously for any degree or diploma at any institution.

I have acknowledged all sources of information and data used in this thesis, and that I have adhered to the ethical guidelines.

Sibahle Zondi

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4 November 2024

Abstract

Technological advances and trends such as connected devices, application of sensors, and online content have resulted in an increase in available data. This has led to an increased importance of big data analytics among researchers and managers, highlighting the value that big data analytics can bring to organizations. The study addresses a significant research gap in understanding how big data analytics capabilities (BDAC) influence service innovation within the context of state-owned enterprises (SOEs). While previous research has extensively explored the impact of BDAC on innovation in private and large multinational organizations, there is limited knowledge on its effects within SOEs, particularly in developing economies like South Africa. This study aims to also fill this gap by analysing the contextual environment by examining the role of institutional pressures in moderating the relationship between BDAC and service innovation.

The purpose of the study is to determine the impact of BDAC on service innovation in SOEs and to provide insights for SOE leaders on how to invest in BDAC to enhance efficiency and performance through service innovation. The research also seeks to uncover the role of institutional pressures in moderating this relationship

A quantitative mono study methodology was conducted, involving a survey distributed to employees in various SOEs in South Africa. The data collected was analysed using statistical methods, including Structured Equation Modelling, Pearson's correlation, Spearman's rho correlation, and linear regression analysis. The results indicate that BDAC has a positive and significant impact on service innovation in SOEs. Among the BDAC components, intangible capabilities were found to have the most significant impact on service innovation. Additionally, the study found that institutional pressures, particularly normative and mimetic pressures, positively moderate the relationship between BDAC and service innovation. Coercive pressure, however, did not show a significant moderating effect.

In conclusion, the study highlights the importance of investing BDAC to drive service innovation in SOEs. It also emphasizes the need for SOE leaders to foster a data-driven culture and organizational learning to maximize the benefits of BDAC. The findings suggest that while institutional pressures can enhance the impact of BDAC on service innovation, the role of coercive pressure is less significant. Future research should explore the dynamic capabilities view of BDAC and its impact on

service innovation over time, as well as the development of a standard BDAC model for different contexts.

Keywords:

Big data analytics, big data analytics capabilities, service innovation, institutional pressure, state-owned enterprise

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1. Introduction to research problem

1.1. Context of the study

Big data analytics capabilities (BDAC) have been found to have a positive impact on innovation, (Côte-Real et al., 2019; Mikalef et al., 2019a; Wu et al., 2020; Niebel et al., 2019; Bhatti et al., 2024; Zheng et al., 2022) however, how this relationship is impacted by contextual factors differs (Mikalef & Krogstie, 2020). Mikalef and Krogstie have argued that the strategies for implementing BDAC may differ depending on the context using the example of large organisations who may benefit more from technology infrastructure, while small firm may require stronger human skills. Contextual factors such as smaller organisations, developing economies and, particularly in the public sector (Clausen et al., 2020) has not been explored. It is noted that research on the impact of BDAC on innovation has been on mostly on private organisations and large multinationals (Mikalef & Krogstie., 2020; Wu et al., 2020) in developed economies, and few studies have been on and small and medium enterprises (Bhatti et al., 2022; Zheng et al., 2022). It is important to ensure efficient understanding of the application of the theorised relationship in different contexts to aid appropriate investment in BDAC.

BDAC has been empirically found to have a positive impact on organisational performance (Yasmin et al., 2020; Mikalef et al., 2019b; Rialti et al., 2019; Ferraris et al., 2019 Akhtar et al., 2019) performance and on various types of innovation as specified in the previous paragraph, but the impact of BDAC on service innovation has not been well researched (Yaşar et al., 2024). There is a research gap on the impact on BDAC on service innovation particularly in the context of state-owned enterprises, which is a different context to privately owned organisations due to their sometimes-conflicting mandate of socio-economic development and financial sustainability, (Butzbach et al., 2022; Goldeng et al., 2008). The SOE context is also argued to have unique institutional pressures (Balakrishnan et al., 2023) which may hamper or encourage the used on BDAC and innovation (Landoni, 2020; Janssen et al., 2017)

1.2. Problem statement

Technological advances and trends such as connected devices, application of sensors, online content have resulted in an increase in available data (Niebel et al., 2019). This has resulted in an increased importance of big data analytics amongst researchers, managers, policy makers and scientists on the value that big data analytics can bring to organisations (Mikalef et al., 2019) which is enabled by BDAC. The ubiquity of business data and analytics capability has resulted in organisations using big data analytics (BDA) to make business decisions (Wu et al., 2020). This has been described as the 'Age of Data.' (Mikalef et al., 2019) due to the high speed and velocity, in which data is being produced and used (Ferraris et al., 2019) as well as the increase in the production of the data, the volume, which is creating more opportunities to improve decision making (Merhi & Bregu, 2020).

The increase in the deployment of BDA has resulted in organisations strengthening their innovation as BDAC are imperative for business improvements (Mikalef et al., 2019; Wu et al., 2019). Mikalef and Krogstie (2020) emphasised the importance of BDAC on innovation and that it is vital for the sustaining competitiveness of organisations. Although a lot of research has been done on BDAC and various types of innovations, research on the impact of BDAC and service innovation is minimal (Yaşar et al., 2024). Service innovation is important because of the advantages of service innovation such as improved customer experience which results in competitive advantage, improvement of operations and the potential for new revenue streams (Yaşar et al., 2024). It is also important for understanding the capabilities required for service innovation and for covering the research gap in the field of innovation (Schymanietz et al., 2022). This is an important gap to cover because services play a crucial role in the global economy (Schymanietz et al., 2022).

Additionally, a lot of research (Bhatti et al., 2024; Zheng et al., 2022; Mikalef et al., 2019a; Wu et al., 2020; Mikalef & Krogstie, 2020) has been conducted to examine the impact of BDAC on different types of innovation, the focus has been mostly on the certain contexts such as in large private organisations. Negating the possibility that the value of BDAC may be less valuable in certain contexts (Mikalef et al., 2019). Huynh et al, (2023) has identified the need for further research in these different contexts due to the varying set of constraints presented by the environment in which

they operate. Clausen et al. (2020) and Bhatti et al. (2022) also supports this, noting the underdeveloped understanding of innovation in the public sector (Clausen et al., 2020), and underdeveloped economies (Bhatti et al., 2024) to understand further how their unique institutional factors impact on the relationship between BDAC and innovation. Furthermore, the topic of big data in public sector is still emerging and requires more research to add value to practitioners (Pencheva et al., 2020)

It has also been found that institutional context of public sectors may hamper big data adoption and therefore leading to minimised innovation despite BDAC being available (Janssen et al., 2017) Furthermore, the level of external pressure or environmental volatility plays a role in sustaining business value, these can be a control in the relationship between BDAC and innovation (Côte-Real et al., 2019). Findings confirm that external pressure or environmental have a negative impact on BDA led business value (Côte-Real et al., 2019).

In developed economies, public sector contributes about 35% to 60% of GDP (Gross domestic product), (International Monetary Fund [IMF], 2024), this has resulted in a growing interest on how the public sector use innovation to improve efficiency (Arundela et al., 2019). In South Africa, government spend as a percentage of total GDP was recorded at 32,47% in 2022 and was estimated to increase steadily to 33.83% by 2028 (Statistic South Africa [SSA], 2024; IMF,2024). State owned companies contribute an average of 13% in the last 5 years (IMF, 2022). SOEs' operations are an important determinant of the productivity and the competitiveness of the economy (Wong., 2018). Although SOEs operate in the market, as they engage in commercial activities, with private companies in providing goods and services, they are exposed to different context and institutional pressure (Balakrishnan et al., 2023). Additionally, the performance of SOEs has been found to also depend on the market structures, Goldeng et al. (2008) has highlighted that as performance is determined by market structures, for example in the case of monopoly, financial performance may be higher because of higher prices but also this can result in lower quality of services and products. This can thus also be interpreted as market structures having an impact on low level on innovation and is applicable to some South African SOEs which have a monopoly in their industries.

SOEs fulfil an important role in developing many countries and engage economically. In some countries they rank amongst the biggest organisations in the

world and provide with a significant share of the market. Not only providing essential services but also boosting the economy and creating new industries. (United Nations Economic Commission for Africa [UNECA], 2021). In South Africa, SOEs have experienced challenges with regards to their financial performance (UNECA, 2021). Given the inferior performance for some SOEs and their role in the economy which is to provide inputs to business such as electricity, logistics, telecoms infrastructure and financial capital (IMF, 2022). This has resulted in the question on whether BDAC can be used to drive innovation and thus performance in their context arising. SOEs are the bedrock of the economy with private companies also relying on them for services and products such as rail, electricity, and private sector funding. This means that the performance of SOEs has a direct substantial impact on the economy (Wong, 2018).

1.3. Purpose statement

The research aims to determine what the impact of BDAC is on service innovation in SOEs. This research will assist leaders in SOEs in their quest to invest in BDAC to improve their efficiency and performance through service innovation. The research will also uncover the role of institutional pressure in moderating the impact of BDAC driven service innovation.

The research will address a gap in theory where BDAC led innovation has assumed the benefit of financial performance gain applicable to private organisations. There is a theoretical need to expand the theory to cover instances where financial performance is not necessarily the end goal. In the case of service innovation where improvement of services and development of new services, may not result in financial performance but fulfil other service delivery and socioeconomic mandates, whether service innovation can be enhanced through BDAC in that context. The institutional pressure experienced by private organisations in BDAC led innovation is different as it can be led by external pressures like competitors (Hasan et al., 2024) which is less experienced by SOEs.

The research will consider the impact of BDAC investment and assist in the navigation of external pressure. While a lot of researchers have found a positive correlation between BDAC and innovation, others have argued that investment in BDAC may not necessarily lead to performance as this relationship is mediated by other variables (Bahrami & Shokouhyar, 2022). It is important for policy makers, managers in SOEs to understand how BDAC capabilities affects service innovation

where competition is not a factor and further learn how institutional pressure can hamper or enhance their service innovation.

1.4. Significance of the study

Practically, integrating BDAC with scenario planning, we can create a range of predictions on how a system will react to various policy decisions. This approach ensures a high level of precision and offers a verifiable, scientific foundation for decision-making in complex systems (Ferraris et al., 2019). Di Vaio et al. (2022), have also stated that public sector in developed countries can benefit immensely from the use of big data, which will result in improved operational efficiency. Like Ferraris et al. (2019) they, Di Vaio et al. (2022) have also cited the decision making and improved scenario planning. There is therefore a need to determine how BDAC can impact the decision making required to improve service delivery through service innovation.

1.5. Delimitations

The research study will focus on Big Data Analytics Capabilities and the impact on Service Innovation in State-Owned Enterprises in South Africa. Much of the literature reviewed on the context is on public sector innovation, the scope of the research is narrowed down to only State-Owned Enterprises within the public sector. The main difference being that general public sector can include enterprises that are not profit drive while state-owned enterprises are profit driven. All while its shareholder, the state, is interested in profits it is also interested in providing a basic service to the people. They are also used as a tool for non-economic benefits such as employment and social issues (Goldeng et al., 2008).

For this reason, to further scope the study appropriately, the focus of the study is the public entities which is defined by the Public Finance Management Act (PFMA) to be government owned business which are schedule 2. These SOEs are independent entities and are either partially or fully owned by the government, with the dual purpose achieve the socio-economic goals of government and a commercial and developmental goals.

1.6. Structure of the research

The report will follow the following structure. The next chapter, chapter two, will review literature on what is known on the research constructs and what is not known, ascertaining the need for the research. This will build into chapter three with will formulate the research hypotheses. Chapter four will detail the methodology that will be followed to collect data and to analyse the data collected. Chapter four will also incorporate the defence and justification of the methodology chosen. Chapter five will be a presentation of the data collected and the results of the data analysis. The discussion of the results presented in chapter five will be in chapter six and finally chapter seven will conclude with the findings and the implications of the findings and opportunities for future research.

2. Literature review

2.1. Introduction to literature review

The literature review is conducted to understand the existing research on what the impact on BDAC is on service innovation. To get to this point, the literature review started off by looking at the context of service innovation in the context of SOE. It unpacks the importance of SOEs and the challenges they face and differences they experience in the context of service innovation.

To study the output construct, service innovation, a broader look into innovation literature is first taken to understand the landscape of innovation and to identify the need for a focus on service innovation as well as to understand what sets it apart from other types of innovation. A broader innovation view was also taken due to the limited research on service innovation but also due to its intricacy with other types of innovation, process innovation, product innovation (Barras, 1986) and supply chain innovation. The literature on service innovation and how it finds expression in a State-Owned Enterprises is then explored. It then further looks at what is known about the relationship between BDAC and innovation and service innovation and identifies the difference with this relationship of BDAC to service innovation particularly in State-owned Enterprises.

Thereafter we look at Big Data as a concept and how it transcends to BDAC. The characteristics of Big Data are reviewed and how different researchers have packaged them over years and settling on the '5V' characteristics. To study the independent construct, which is BDAC, different literature is reviewed to understand the BDAC and its components as theorised and applied by different authors. This study has settled on the components of tangible, intangible, and the human skills as the components or subconstructs that enable BDAC.

The literature review then investigates the impacts of institutional pressure by looking at the research on coercive, mimetic, and normative pressure on the relationship between BDAC and service innovation in SOEs. Where some cases it may positively impact the relationship between BDAC and service innovation and in some cases, it may negatively impact it. The research looks at the theories that underpin the studies of the BADC and its relation to innovation and performance. The literature is underpinned by the Resource Based View (RBV) theory as it is

often used as the theory that looks at internal resources that focuses on internal resources that determine competitive advantage of an organisation or an industry.

2.2. Contextual setting

SOE can be defined as organisations that operate in the market and are owned by the state. (Butzbach et al., 2022; Christiansen, 2011). They have a mandate of economic and financial sustainability while also having a mandate to fulfil the socioeconomic requirements of the country (Butzbach et al., 2022; Goldeng et al., 2008; UNECA, 2021). SOEs are an essential instrument of the state for the control of the economy (Butzbach et al., 2022). There has been a perspective that the government uses SOEs to achieve certain economic policies and even innovation, social, economic growth and politics, which has led to the belief that SOEs are highly controlled by the government (Butzbach et al., 2022). State ownership may also be due to various types of market failures and is seen as a means to achieve non-economic objectives, such as ensuring public control over natural resources, implementing regional policies, addressing employment concerns, and tackling social issues (Goldeng et al., 2008). There is also however an argument that there is a nuanced view where SOEs can exercise agency and autonomy by independently pursuing institutional change through the leveraging of resources from their close relationship with the state and with other stakeholders (Butzbach et al., 2022).

Although SOEs operate in the market, as they engage in commercial activities, with private companies in providing goods and services, they are however exposed to different context and institutional pressure (Balakrishnan., 2023). Additionally, the performance of SOEs has been found to also depend on the market structures, Goldeng et al. (2008) has highlighted that performance is determined by market structures, for example in the case of monopoly, financial performance may be higher because of higher prices but also this can result in lower quality of services and products. This can thus also be interpreted as market structures having an impact on low level on innovation and is applicable to some South African SOEs.

Some scholars have studied the innovative role of SOEs due to their increasing impact in emerging economies, China in particular, as innovation played an essential role (Landoni, 2020). Landoni. (2020) has argued that innovation in SOEs needs to be looked at differently than private companies because of their long-term perspective, public nature, appreciation of externalities that increase social benefits,

and their relationship with the government. As such the context of SOEs, being part of the public sector bring different contextual barriers to innovation, as found to be the law and regulatory requirements (Cinar et al., 2019).

2.3. Service Innovation

The concept of service innovation was first coined by Barras (1986) when he identified the need to theorise service innovation due to the increase in information technology adoption that would change how services are delivered. This initial view of service innovation was based on services industries as the services industries was seen as the key adopters on the new information technology revolution and was seen to be the major driver of the next wave of economic growth (Barras, 1986). Although this study of Barras (1986) was a conceptualisation of innovation in the services sector, it also explains how the integration of other types of innovation as the process develops from process innovation to improve the quality of the service it then leads to the development of new products, which is product innovation. Similarly, business model innovation can be linked to service innovation with respect to the value proposition dimension, which is essentially innovation of the range and the nature of the products and services offered by a business, to create new and enhanced revenue streams (Ciampi et al., 2021). (Ciampi et al., 2021) also stated that BDAC allows organisations to develop new value creation processes which can introduce offering for customers. This thus attests to business model innovation also being linked to process innovation. This leads to a take, to look at innovation more holistically and understand the differences in the different types of innovation to understand the BDAC impact on innovation from a literature review perspective, and then further understand the uniqueness of service innovation which was the focus of this study.

Innovation has been defined as the combination of new and old knowledge to create a new or improved product or process ((Gustafsson et al., 2020; OECD, 2018). There are several types of innovations. Kahn (2018) lists the types of innovation as product innovation, process innovation, marketing innovation, business model innovation, supply chain innovation, and organizational innovation. Service innovation is notably not listed by Khan as one of these but has been defined under product innovation as the creation of new products and services (Kahn, 2018; OECD, 2018). Service innovation is however particularly different from product innovation because of its intangibility, customer co-production, simultaneity, heterogeneity, and perishability

(Troilo et al., 2017). These traits make the organizational context and technology more interdependent in-service innovation than in product innovation. Since services involve interactions among participants, processes, and physical elements, data-rich environments impact service innovation differently. This due to the unique interplay between big data technologies and organizational factors (Troilo et al., 2017)

Service innovation has further been defined as the use of new concepts and technologies to improve existing services and the quality, and efficiency of services or the creation of new services (Feng et al., 2020). Again, to highlight its uniqueness from other innovations, Schymanietz et al. (2022) has identified the commonality in all service innovation definitions to be multitude of factors, organisations, customers, partners and suppliers, interacting and collaborating in an ecosystem. Furthermore, newer definitions denote it as the formulation of a solution to customer needs, which may consist of new or improved systems to offer services in a more efficient way and an improvement in the touchpoints which improves the interaction (De Luca et al., 2021).

The most important to the definition of innovation in general, is the creation and the realisation of value (Chen., 2020). However, service innovation may fail to fit this definition as its success may not always result in realisable monetary value (Gustafsson et al., 2020). Similarly, public service innovation is mostly derived from a private sector perspective negating the public value and collaborative orientation (Chen et al., 2020), and the different drivers which are not market drivers as in private organisations (Rubalcaba & Peralta, 2023). What is concerning for the research agenda on service innovation is the number of scholars who have stated the diversity of views on what service innovation is and the disintegration of theory building in the field (Heinonen & Strandvik, 2021; Furrer et al., 2020; Gustafsson et al., 2020). Hence there has been a shift in perspectives of service innovation from an organisational perspective to customer perspective, on ways to create customer value (Lehrer et al., 2018; Furrer et al., 2020)

Furthermore, the Oslo Manual (OECD, 2018) which is an international guideline for collecting and interpreting innovation data such that it is comparable has had limited focus on service innovation (Arundel et al., 2019). Arundel et al. (2019) examines the measurement of innovation according to the Oslo Manual and public service innovation, noting the start differences such as relevance to policy, lack of profit motive and its collaborative nature.

The increase in the utilisation of data and the availability of big data has opened up a new opportunity of research on how big data interacts with service innovation (Schymanietz et al., 2022). This supports the research gap on the impact of BDAC on innovation when it pertains to service innovation. Troilo et al. (2017) highlights the importance of a being customer focused, having a data-drive culture, strong leadership to support, and BDA led marketing integration for effective service innovation. These factors lend to the components BDAC which is the IT infrastructure and data, the human skills and leadership and the intangible elements such as data driven culture.

2.4. Big data and Big Data Analytics

2.4.1. Big Data

Big Data is large amounts of data that is fast moving and that is instantaneously available (Ferraris et al., 2019) and diverse (Shi, 2022), drawing from different sources such as datasets generated from instruments, sensors, internet transactions, email, video, GPS signals, satellites, social media, or smartphones (Huynh et al., 2023 ; Shi, 2022). There are several definitions of big data and big data analytics, but they converge to two components, the data science component, and the data technology component (Shi, 2022). The technology component refers to it not being able to be processed by traditional technology due to its complexity and its speed (Huynh et al., 2023). While the data science component is the science of extracting and transforming the data, hence big data alone cannot add value without the technology and the analytical science (Huynh et al., 2023). While some scholars have defined Big Data using data characteristics, Big Data alone is not useful without the role of analytics that graduates it to unlock value and insights (Garmaki et al., 2023).

2.4.2. Big Data Analytics

BDA is the interplay of the two, using the data technology and the data science to extracts insights (Shi, 2022). As such BDA definition is a process of managing, processing, and analysing data to extract insights and value (Huynh et al., 2023). Big Data Analytics is characterised with the dimensions specified by a number of V's from "3V's" (Sagiroglu & Sinanc, 2013) which is Volume, Velocity, Variety, other authors have added, the 4th V, Value (Chen et al., 2014; Shi, 2022; Mikalef & Krogstie, 2020) and ultimately "5 V's", which is the volume, variety, velocity, veracity, and value

(Merhi & Bregu, 2020; Wamba et al., 2017; Ferraris et al., 2019). Some authors, (Hasan et al., 2024; Rialti et al., 2019; Bag et al., 2021) have extended the definition to “7V’s” to include visualisation and variability. This view by of “7V’s” is not widely used in big data literature. In this regard the theory will focus on the “5V’s”, where “Volume” indicates the enhanced quantity of data, “Velocity” refers to the speed of collection and processing of data. “Variety” is the different types of data, structured, semi-structured and unstructured and “Veracity” is the quality and the improved reliability of data and lastly “Value” is the information and insights that enable strategy (Bahrami & Shokouhyar, 2022).

2.4.3. Characteristics of Big Data ‘5V’

Volume

The volume of data has become so large, larger than terabytes and petabytes, resulting in traditional methods of storing and analysing to be insufficient (Sagiroglu & Sinanc, 2013). This characteristic of big data is always the first to listed and explained in literature. The increase of data volume has been fuelled by the digitization (Huynh et al., 2023). This is due to technological advances which has increased quantity of data (Ferraris et al., 2019).

Velocity

The velocity means that data must be collected, processed, and analysed speedily (Chen et al., 2014). Velocity is not only an imported characteristic for the sake of big data but more importantly for speed of processes as it presents more commercial value if used as quickly as possible (Chen et al., 2014; Sagiroglu & Sinanc, 2013). In most cases the speed tends to be more important than the volume as it allows an organisation to be react faster and therefore be more competitive (McAfee & Brynjolfsson, 2012).

Variety

Variety of data is the type of data, which is structured, unstructured and semi-structured. Structured data is data that has been tagged as it enters a data warehouse and can therefore be sorted immediately. (Sagiroglu & Sinanc, 2013). Unstructured data is random and cannot be easily sorted (Witell et al., 2016) examples are audio, video, and webpage (Chen et al., 2014). Variety is brought about by the digitization which introduces various digital information which fits the category of unstructured (McAfee & Brynjolfsson, 2012).

Veracity

Veracity is the accuracy of data and the extent to which the data can be trusted. Part of trusting the data is removing biases and doubts and opportunities for fabrication of data. This big data characteristic is a way of expressing the reliability for analysing and subsequently making decisions. (Sivarajah et al., 2017)

Value

The value characteristic of Big Data is challenging as it amplifies the true potential of big data which is to provide actionable insights and decision making. This occurs through the management, processing and analysing of the big data. (Sivarajah et al., 2017). To get the value from big data (Mcafee & Brynjolfsson, 2012) identified five challenges that organisations face in extracting value and benefiting from big data. The challenges are top management, human skills, technology and decision-making culture. As such, research on BDAC has grown to understand what the BDAC to exploit the benefits of BDA, which is innovation and organisational performance and a sustainable competitive advantage (Mikalief et al., 2019; Ferarris., 2019).

2.5. Big Data Analytics Capabilities

BDAC is defined as an organisations ability to use big data through the right technology, skills, and structures, by capturing and analysing it to generate actionable business insights for innovation and business value (Akhtar et al., 2019; Fosso Wamba et al., 2020; Ciampi et al., 2021; Zheng et al., 2022; Huynh et al., 2023). Some authors have categorised BDAC into three main categories which is infrastructure, human resources, and management (Yasmin et al., 2020; Rialti et al., 2019; Bag et al., 2021; Aljumah et al., 2021). Human resources focus on the technical skills like, programming, data science, and data analytics skills (Bag et al., 2021). The presence of this skill in an organisation is critical because it improves the chances of adoption of the BDA, in the form of new information and it also improves the existing infrastructure (Rialti et al., 2019; Aljumah et al., 2021). The management speaks to the strategic capability to lead a conducive organisational culture for BDA to thrive, which is the ability to make strategic decisions like getting the right skills and policies to drive BDA (Bag et al., 2021; Yasmin et al., 2020). While these three components of BDAC work together it seems they may not be equal and have different challenges, Yasmin et al. (2020) states that the technical challenges, which

is the infrastructure, may be large but the management challenges are even more complex. This view is supported by (Rialti et al., 2019) in saying that the management capabilities are critical in that they are required to select and manage the right infrastructure for the organisation and well as ensure that the right human skills are in place.

Other researchers such as Ciampi et al. (2021) and Mikalef et al. (2019) have drawn from IT literature to categorise BDAC as tangible, intangible, and human skills. Tangible capabilities are aligned to the infrastructural capabilities to warehouse, manage, and analyse big data, including the financial and time resources (Ciampi et al., 2021). Intangible resources are the data driven culture in an organisation that enables the use of BDA (Ciampi et al., 2021) and the organisational learning capability of an organisation (Mikalef et al., 2019b). Human skill is both the technical skills and the management skills (Ciampi et al., 2021).

In this regard there are similarities between intangible and management capabilities in the previous classification of BDAC, however the intangible resources are more explicit in their emphasis on the organisations data driven culture and organisational learning. As drawn from the IT literature the human skills capabilities are set out separately to include both technical skills and management skills. This makes the resources combination to be socially complex as BDAC are a combination skill, technical and managerial in coordination (Mikalef et al., 2019b). This also results in the requirement of blending the technical and managerial skills whereby the data-analytic thinking competency does not only sit with data scientists but is present throughout the organisation and particularly in managerial and decision-making positions (Mikalef et al., 2019b).

The research will focus on the BADC model drawn from IT literature, tangible, intangible and human skills, because it emphasises the importance of intangible resources and separates that from management capabilities. It also sets out the human capabilities, both management and technical as one component. This can be considered as an important combination as it has been established that on one hand managerial capabilities drive the technical capabilities and infrastructural capabilities by hiring the right people and ensuring that technological infrastructure is in place (Rialti et al., 2019; Yasmin et al., 2020). It has also been said that the technical human skill is important in ensuring an improvement of infrastructure and the improving the likelihood of BDA use (Aljumah et al., 2021; Rialti et al., 2019). This

may then be viewed as that, the human resources skills of BDAC are more important in organisations. This view is supported by (Akhtar et al., 2019) who found that while a number of researchers have highlighted the importance of tangible BDAC such as the technology infrastructure for gaining competitive advantage, to be able to leverage that technology, there is a need for specialised technical skills and cross functional collaboration. They also add the importance of cross functional team collaboration applying their diverse skills to extract value form big data (Akhtar et al., 2019). The cross-functional collaboration aspect highlighted by Akhtar et al. (2019) lends to the intangible BDAC of an organisation which is similar to the recommendation by Mikalef and Krogstie, (2020) highlighting the relative importance of intangible BDAC and that managers should drive a cultural shift to promote the use of BDA and intelligence, integrating evidence-based decision-making into the fundamental operations of the business. Nevertheless, the call for managers to be the drivers of the use of BDAC is thus still emphasising a higher relative importance of management capabilities. It can therefore be argued that of all the BDAC capabilities, the human skills capabilities have the biggest impact on innovation as they can influence the big data technology and the right culture to drive the use of BDA.

2.6. Big data analytics capability and innovation

Research on the impact of BDAC on innovation has been done by several scholars focusing on different types of innovation such as, incremental, and radical innovation (Mikalef et al., 2019), product innovation (Niebel et al., 2019), process innovation (Mikalef & Krogstie., 2020), business model innovation (Ciampi et al., 2021) and supply chain innovation (Wamba et al., 2020; Bahrami & Shokouhyar., 2022; Hasan et al., 2024), with the later referring to value chain innovation as optimising supply chain operations. The findings from previous research on the relationship between BDAC and innovation is consistently showing a positive correlation of BDAC with innovation. Although this relationship is well researched, there are still opportunities for further research due to the complexity of BDAC and that most studies cover limited geographical locations which are in developed countries (Huynh et al., 2023).

Research has shown how the positive impact of BDAC on innovation, mediated by other factors such as dynamic capabilities. (Mikalef et al., 2019b). Xiao et al. (2020) evaluated the moderating effect of environmental dynamism on the relationship

between BDAC and service innovation and found it to have a negative effect. However, in a study Mikalef et al. (2019a) looked at how the relationship between big data analytics is impacted by environmental factors, dynamism, heterogeneity, and hostility. and the empirical finding reveals the increased relevance of BDAC when these conditions in the environment exist because managers can no longer rely on their own knowledge but rely on real time BDA which enabled them to understand the complexity of the environment better. Therefore, although environmental factors have a negative impact on the relationship between BDAC and innovation, the presence of BDAC is even more relevant in these environmental conditions because the impact of the uncertainty is reduced.

Dubey et al. (2019a) found the moderating effect of organisational agility on the relationship between BDAC and supply chain agility is positive. They defined supply chain agility as an organisations ability to deliver innovative products effectively and efficiently (Dubey et al, 2019a). Others have highlighted the indirect nature of the effects of BDAC on innovation and performance as mediated by other organizational capabilities (Mikalef et al., 2020). While the study by Mikalef and Krogstie, (2020) considers contextual factors it focusses on large revenue generating companies in Norway and the authors take note of the lack of generalisability. Taking all this into consideration it is therefore important to expand the research of the relationship between BDAC and innovation into other contexts to firstly test the relationship and then to evaluate the effect of other factors in different contexts.

On Service innovation, there is a notion that BDA technology has significant potential for service innovation and identifies the key factors relevant to creating new value propositions (Lehrer et al., 2018). These factors are identified as automating customer-sensitive service delivery and combining human and tangible elements in customer-sensitive service practices (Lehrer et al., 2018) . These roles are rooted in the infrastructure capability off BDA. There have been arguments that BDA creates opportunities for innovation in the development of services (Bahrami & Shokouhyar., 2021). Contrary to this Xiao et al. (2020) has argued that there has been some unsuccessful value extraction from BDA to support service innovation, they stated that an overfocus on BDA market data is not sufficient to drive service innovation. A recent empirical study by Yaşar et al. (2024) found that BDAC have a positive impact on service innovation. Although the study specifically focuses on service innovation as it is in service industries, which may be limiting as there is also a view that service innovation is not restricted to service organisations but extends to the servitisation of

product-based business offerings (De Luca et al., 2021).

Servitisation is the use of digital technology in the creation of innovative services to capture value (Raddats et al., 2022). The servitisation has been largely driven to big data technology, such as cloud computing and the high volume of data and analytics to improve innovating services (Schymanietz et al., 2022) and competitive advantage (Raddats et al., 2022). De Luca et al. (2021) found in their study that the difference between services industry and product-based industry has become small as it pertains to service innovation due to the advancements of BDA. The example is made on how Internet of Things (IoT) can be used in manufacturing organisations to identify opportunities for innovative services. This view is creating a full circle view as it pertains to innovations definitions (Kahn, 2018; OECD, 2018) which combines the product innovation and service innovation as the creation of new products and services. For this reason, this study will focus on service innovation in SOEs in both manufacturing services and services industry.

Companies are apportioning a significant percentage of their technology budget on digital technologies to aid BDA, making it crucial to understand the contexts under which BDA can be transformed into innovation (Bhatti et al., 2022). In most studies, the positive correlation of BDAC with organisational performance is also seen as innovation performance (Upadhyay & Kumar, 2020; Brinch et al., 2021) This means that a positive impact BDAC on innovation can be inferred to organisational performance.

2.7. Institutional pressure

According to Institutional Theory proposed by DiMaggio and Powell (1983), which is routines norms and rules influencing social behaviour in organisations through their guidelines. Institutional pressures are more specifically described by three types; coercive, mimetic, and normative (Dimaggio & Powell, 1983; Behl et al., 2022). Coercive pressure is from other organisations and regulatory bodies, mimetic is pressure to imitate successful strategies due to risk and uncertainties and normative pressure can be from professional bodies (Dimaggio & Powell, 1983; Behl et al., 2022)

2.7.1. Coercive Pressure

Coercive pressure (CP) can originate from government regulations and policies, industry and professional networks and associations. It can also be applied by organisations on whom a company depends on and can be formal or informal pressure (Dubey et al., 2019b). Dubey, et al. (2019b) have stated that social pressure can impact an organisations choice of technology, they have further stated that legislation on data privacy limits what data can be collected and how long it can be stored, which imposes limits on personalising the data as this may face ethical scrutiny.

2.7.2. Mimetic Pressure

Mimetic pressure (MP) arises from competitor activities (Dubey et al., 2019b; Bag et al., 2021) and thereby organisation mimic competitors due to uncertainty of the competition pressure (Dubey et al., 2019b). DiMaggio & Powell, (1983) had argued that mimetic pressure (MP) occurs as a results organisations mimicking without the full understanding of technologies, citing that the uncertainty may leave organisations desperate to be remain successful. Dubey et al. (2019) have argued that when it comes to BDAC, organisations tend to observe and adopt what they can from successful competitors and that tends to be based on BDA decision making before taking action.

2.7.3. Normative Pressure

Normative pressure (NP) originates from the professionalisation of individuals in industries to legitimise their status, reputation, and their existence (Hasan et al., 2024) and may opt to choose and the transfer of practices from one organisation to another (Dubey et al., 2019b). NP can be a driver for an organisation to use systems with external data to ensure they are included in cooperative relationships and access to other industry resources (Dubey et al., 2019b). Driven by the need for an organisation to operate in an acceptable way, normative pressure considers the moral aspects to legitimise themselves by getting technologies that conform to the status quo over economic benefit. Behl et al. (2022) on the contrary recognises the impetus that institutional pressure can impose to use new technologies and frameworks. Similarly in their study Bag et al. (2021) argue institutions pressures force organisations to develop their resources to gain competitive advantage. Suggesting that there is also a positive effect to driving positive change in an organisation. Dubey et al., (2019b) argues that the behaviour of an organisation is driven more by the need for legitimacy and less by competition and aspiration to be

more for efficient.

This warrants the need to understand the effect of institutional pressure on the relationship between BDAC and innovation. Even more so in the context of SOEs as Balakrishnan et al. (2023) have added that there is greater pressure from state-owned enterprises to maintain legitimacy with government as evidenced in their comparative study. This institutional pressure is seen to influence managers in their decision making, to be consistent with institutional norms (Balakrishnan et al., 2023).

2.8. Resource Based View

The literature review will draw from the Resource Based View (RBV) theory (Barney, 1991; Barney, 2001), which considers what capabilities are critical for an organisation to conduct its operation and claim its competitive position (Ferraris., 2019). The RBV looks at the combination of resources used together to create a competence. For the resources of an organisation to give it competitive advantage it has been conceptualised to fit the VRIN criteria, which is valuable, rare, imperfectly imitable, and non-substitutable (Barney, 1991). The RBV has been used by numerous researchers studying BDAC (Bhatti et al., 2022; Ferraris et al., 2019; Mikalef et al., 2019). BDAC capabilities are a combination of resources, tangible, financial, infrastructure and intangible, organisation culture, and human resources which is skill such as data science, data analysts, strategic leaders (Dubey, et al., 2019b). This BDAC fit into the RBV theory which makes it the appropriate theory to use.

In business management studies RBV is mostly used for BDAC but with limited depth into the theory (Huynh et al., 2023). The resources-based view holds the argument that some resources and capabilities cannot simply be bought or sold but are developed over a long period of time (Barney, 2001). This makes it the perfect theory to underpin this study as this is true for BDAC. The intricacies of interpersonal relationships, the organisational culture, the reputation with customers and suppliers and the capability to process information is a unique combination for each organisation and cannot simply be copied (Yasmin et al., 2020). This gives rise to the requirement for organisations to build these capabilities from scratch.

The intricacies expressed, speak to the tacit nature of BDAC as explained by Bag et al. (2021) that BDA technical skills such as programming and data analysis skills, are invisible and take a long time to harness. The intangible resources in BDAC speak to the organisational learning and data driven culture of an organisation. The value of BDAC and its ability to foster organisational learning has been defined as the “hidden value” (Garmaki et al., 2023). This is also true about the big data management skills which need time to gain inter-personal trust and good relations with other functional managers (Dubey et al., 2019b). This is supported by Akhtar et al. (2019) by saying the that the human skill is not merely the technical skill that sits with individuals, but collaboration between various functions to create value. This is described as the “bundling” of the human skills (Akhtar et al., 2019). This speaks to the imperfectly imitable component of RBV, as while the skill can be bought, the bundling of the skill with other skills in the organisation cannot be imitated or transferred.

2.9. Big data analytics capabilities and innovation in state-owned enterprises

In their research, Klievink et al. (2017) stated the view was that private sector is going ahead with big data use while the public sector seems to be delaying despite the extensive potential that big data hold for public organisations. The potential for big data is in that it could improve efficiency, effectiveness, and transparency, it could further improve services (Klievink et al., 2017). In support of this notion, Andrews (2019) has also supported the notion of a neglect to technology in the public sector with big data presenting a challenge to this status.

Landoni (2020) has started that there is less efficiency in SOEs thus the lower performance compared to private sector and have also linked this to a more administrative focus, risk aversion and a focus on short term goals. Although a different view presented is that the access to patient capital and guarantees through the state can support innovation for SOEs (Landoni, 2020). Similarly, a study by Boudreaux, 2024) found that SOEs are more innovative than Private-Owned Enterprises (POE's) when they are not in market orientated provinces.

The impact of market structures on the performance and innovative behaviour of SOEs has been considered by Goldeng et al. (2008) where they found that the

performance of SOEs to depend on the market structures, for example in the case of monopoly financial performance may be higher because of higher prices but also this can result in lower quality of services and products. This can thus also be interpreted as market structures having an impact on low level of innovation and is applicable to some South African SOEs.

State-owned enterprises (SOEs) are deeply integrated into institutional framework as they often gain increased political legitimacy with the expectation to align with government policies and ideologies, whether these aim to change or maintain the current institutional environment. (Butzbach et al., 2022)

2.10. Conclusion of literature review

The literature review focused on the construct of BDAC and its relationship with innovation while highlighting the limited research on the relationship with service innovation. This has highlighted the need for a study in BDAC and service innovation, particularly in SOEs where while operating in the market may be exposed to different market structures. Moreover, it also highlighted the change in the concept of service innovation and its meaning in the context of the public sector. This further gives rise to the need to evaluate the relationship between BDAC and service innovation. The literature review also looked at the different context of SOEs the potential impact of the institutional pressures withing the context on the relationship between BDAC and service innovation.

3. Research questions and hypotheses formulation

The research questions driving this study is “What is the impact of BDAC on service innovation in the context of SOEs”. The previous sections on the research problem and the literature review have identified a research gap in the impact of BDAC on service innovation. This shift in perspective on service innovation (Furrer et al., 2020) and the sometimes-non-monetary value (Gustafsson et al., 2020) that is achieved by service innovation and more so in the context of SOEs where the context is not always driven by competition confirms the need to test the relationship between BDAC and service innovation. This then leads us to the first research question below.

Question 1: What is the impact of BDAC on service innovation?

There has been a lot of studies providing empirical evidence for a positive impact of BDAC on different types of innovation. The impact of BDAC on service innovation has been limited. A study on the impact of BDAC on service innovation has shown that the impact is positive, it was however limited to service innovation as innovation in a service industry (Yaşar et al., 2024). The first hypothesis is therefore form as follows.

H₁: Big Data Analytics Capabilities (BDAC) are positively correlated to service innovation.

Big Data Analytics Capabilities is made up of a combination of components, tangible which is the technical data processing capabilities and capital and time to implement big data projects. Intangible capabilities which is a data-driven culture to adopt BDA and the ability to learn and grow from the insights and the human skills, which is the managerial skills and the technical skills.

While the three components may have originated from IT capability, they each have their core aspects and relevance within the big data context. (Huynh et al., 2023) has advocated for further research in each of the components, as all of them are particularly valuable for accommodating various contexts of big data usage, where the importance of each component can vary, or additional dimensions may need to be incorporated.

Question 2: What are the factors of BDAC Capabilities (intangible, tangible, and human skills) that have an impact on service innovation.

The three components of BDAC work together, however it seems they may not be equal and have different challenges, Yasmin et al. (2020) states that the technical challenges, which is the infrastructure, may be great but the management challenges are even more complex. This view is supported by (Rialti et al., 2019) in saying that the management capabilities are critical in that they are required to select and manage the right infrastructure for the organisation and well as ensure that the right human skills are in place. Additionally, it is also found that the presence of this skill in an organisation is critical because improves the chances of adoption of the BDA, in the form of new information and it also improves the infrastructure (Rialti et al., 2019). These two together, management skills and technical skills are put together in the IT led capabilities model of BDAC which is used in this study as human skills. The second hypothesis is therefore formed as follows. The important of the human factor is also highlighted by Mikalef and Krogstie (2020) as they noted the importance of the technical and the management skills in deriving business value for big data projects. With the emergence of specific big data skills, such as data science which a critical in understanding the value of data and what processing is required to exploit the value. These two together, management skills and technical skills are put together in the IT led capabilities model of BDAC which is used in this study as human skills. The second hypothesis is therefore formed as follows (Mikalef & Krogstie, 2020).

H₂: The relationship between human skills and service innovation is stronger than the relationship between intangible and service innovation, and tangible and service innovation.

BDAC enables organisation to make decisions to innovate products and services, however those decisions may be impacted by the institutional context as (Dubey et al., 2019b) has argued that the need for legitimacy is a greater driving force for organisation than the need for performance. In SOEs the limited competition compared to private companies makes this study even more relevant due to the greater institutional pressure (Balakrishnan et al., 2023). The question of how the relationship between BDAC and service innovation is moderated by institutional pressure is not known. This leads to the second question below.

Question 3: What is the moderating effect of institutional pressure on the relationship between BDAC factors and service innovation.

Institutional pressure is evident more so in the context of SOEs as Balakrishnan et al. (2023) have said that there is greater pressure from state-owned enterprises to maintain legitimacy with government as evidenced in their comparative study. This institutional pressure is seen to influence managers in their decision making, to be consistent with institutional norms (Balakrishnan et al., 2023). Institutional pressure may be limiting to the relationship between BDAC and innovation as organisations and may opt to choose technologies that conform to the status quo over economic benefit Behl et al. (2022). This then leads to the third hypothesis as follows.

H₃: Institutional pressure has a negative moderating impact on the relationship between BDAC and service innovation.

The figure below is an illustration of the research model showing the three hypotheses.

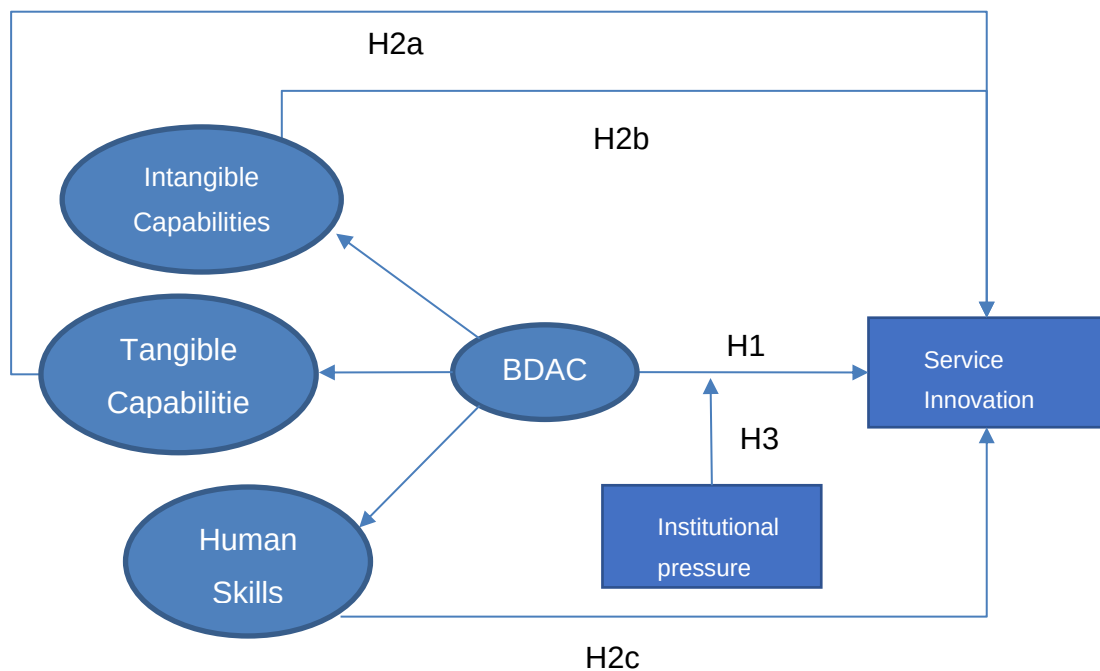


Figure 1: The theoretical research model.

The following section will explain the methodology that was followed to answer the research question and thus test the three research hypotheses.

4. Research design and methodology

The purpose of the research methodology is to get empirical evidenced answers to the research questions. The purpose was achieved by testing the constructs, BDA capability, service innovation and the relationship between these constructs. It is also to examine the moderating effect of institutional pressure on the relationship between these constructs. The research is descriptive study as it aims to describe the relationship between BDAC and service innovation (Saunders & Lewis, 2018)

4.1. Research Paradigm

4.1.1. Philosophy

The research philosophy will be positivism as the study aims to test the relationship between BDA capability and service innovation based on existing findings from other researchers (Mikalef et al., 2019a; Mikalef et al., 2020; Wu et al., 2020). The study is also collecting new knowledge in a different context using empirical evidence (Rahi, 2017). The existing literature is used to determine the behaviour in the given context. The study looks at observable constructs because BDAC can be observed and can be confirmed to exist irrespective of interpretation or bias (Saunders & Lewis, 2018). Service innovation is also a construct that can be observed and confirmed to exist. The relationship between the two therefore can be evident and observable using statistical analysis, and this brings credibility to the study (Saunders & Lewis, 2018).

4.1.2. Approach selected

Since the rise of big data, several studies have been done on BDAC. Theoretic propositions exist on the relationship between BDAC. The approach will be deductive as it is to test an existing relationship (Saunders & Lewis, 2018). The research aims to verify a theory by collecting the quantitative data from respondents and determine the results through the use statistical tests (Rahi. 2017). According to Rahi (2017) a deductive method is suitable for studies where the researcher creates a hypothesis, and then tests the hypothesis. The research hypotheses formed for this research is based on existing literature hence the deductive methodology (Upadhyay & Kumar, 2020).

4.1.3. Methodological choices

The choice of methodology for this study is a mono study as it will employ one method of data collection. The mono study was sufficient to test the constructs and the relationship between them because the constructs have been empirically tested in different contexts. Notable researchers in the field have also used a mono study (Mikalef & Krogstie., 2020;Dubey et al., 2019b). In some cases, multiple method, including secondary data (Wu et al., 2019) was used, but to measure product innovation. In another case a mixed method was used (Mikalef et al., 2019a) where case studies were included additional to the qualitative study, but to test the relation between BDAC and organisational performance. While there may be an advantage in employing a multiple or mixed method to uncover the nuances and to gain a better understanding in the different contexts the time scale of this study does not allow for a mixed method.

4.2. Research strategy

The research strategy was based on the research philosophy, the methodology chosen and the other recent studies in these constructs, as such the research instrument of a questionnaire-based survey (Saunders & Lewis, 2018). The method of electronic survey is beneficial because it provides flexibility and can reach a much larger and geographically spread audience than a manual survey (Roberts & Allen, 2015). The research methodology that was used for this study was a quantitative methodology. The quantitative methodology is appropriate for this study because it aims to measure existing and quantifiable constructs.

The survey started with a qualifying question which was to test if the respondent works for an SOE or not. Respondents who respond that they do not work for an SOEs responses were removed from the dataset. The next set of questions were demographic questions. Although the demographics are not used as controls in the study and therefore not needed to answer the research questions. The demographic questions were used to pick up trends related to demographics but were also used to check that the sample is not biased to a demographic (Ray, 2020).

The survey questions were adapted from scholars who have tested the constructs and have published in rated journals and can be found in APPENDIX A. For BDAC, questions were adapted from Dubey et al. (2019b) and Mikalef et al. (2019a), for the construct of service innovation, survey questions were adapted from Xiao et al. (2020) and Bahrami and Shokouhyar (2022). For the moderating construct institutional pressure, questions were adapted from Dubey et al. (2019b). A questionnaire-based survey is suitable because it allows for the investigation of several factors and the results can be generalisable (Fosso Wamba et al., 2020; Mikalef et al., 2019b), additionally it also allows for consistency and repeatability in measuring the outcomes (Saunders and Lewis., 2018). Using a questionnaire-based survey adopted from previous studies also offers a longitudinal element to the field of study because the results will be measured at a different time and can therefore capture the changes over time.

The time horizon of the study was cross-sectional. The survey was sent out at one time for respondents to complete. This was given us a snapshot of the current situation. While there might be some value in doing a longitudinal study, given the fast-changing pace of BDA and its ability to accelerate decision making, the time available for this study did not allow for a longitudinal study.

4.3. Population

The survey was sent to employees in SOEs, in schedule 2 of SOEs. Mikalef et al. (2019) highlights the importance of not limiting BDAC to data-analytic thinking, only but to expand it throughout an organisation, especially to management level. The reason for this is because BDAC and innovation is not limited to IT professionals. While some studies (Mikalef et al., 2019; Wu et al., 2020) testing for BDAC have focused on IT professionals and senior leaders such as Chief Information Officers (CIO), the ubiquity of BDA in the recent years has motivated to open the study to more professionals such as data analyst, business analysts and decision makers in operations and customer service. Ferraris et al. (2019) has also supported this view and states that a return on investment in big data would not be fully exploited if employees at lower levels do not have the ability to understand data and make data driven decisions. This is aligned to the definition of BDAC, as a holistic process that involves the collection, analysis, use and interpretation of data, to create business value (Bhatt et al., 2022), and therefore their focus in the population was of top and middle-tier managers not just in the IT space (Bhatt et al., 2022). Similarly, Wamba

(2020) targeted senior level analytics professionals with experience of business analytics. Questions were asked simplistically, and terminology was explained to ensure consistent understanding and interpretation, and thereby improving the validity of the sample.

The number of SOEs in South Africa depends on the breath of the definition. This can depend on the % state shareholding and government control, the level of the SOE, i.e., provincial, or national, other definitions can also include profit making or government agency etc. It is noted that different countries define SOEs differently. According to the South African Government website, South Africa has 123 state-owned and public enterprises (South African Government [SAG], 2024). The study focused on schedule 2 SOE which is only 21 SOEs as defined by the PFMA.

The unit of analysis for the study is state-owned enterprises. The aim will be to determine if state owned companies leverage big data analytics capability to drive service innovation. This ensure that respondents in different areas of a single enterprise may be considered as having different experiences. These different experiences may be driven by the institutional factors.

4.4. Sampling method and sample size

Non-probability, purposive sampling was be used. The sample is non-probability sample as there is no complete list of employees in in schedule 2 SOEs (Saunders & Lewis, 2018). Therefore, each SOE employee does not have a probability of being included in the sample (Pandey & Pandey, 2015). The purposive method is used to ensure that the respondents are within the confines of the context being tested and those that can help answer the research questions (Sanders & Lewis, 2018). The method is also purposive in that it was distributing to networks to as many different SOEs as possible so that the sample was most representative of SOEs as whole and not concentrated in a few. The employees working for state-owned companies were be accessed using existing networks and through LinkedIn. Snowballing was also used to reach a wider audience of SOE employees by asking my contacts to also share the surveys with SOE employees that they have in their networks. It is important to get the correct sample size to ensure that the results obtained can be inferred on the population (Rahman, 2023).

There are multiple methods to determine the appropriate sample size of a

quantitative study. Some of the methods to determine the suitable sample size such as the Cochran's (Bartlett et al., 2001) require a population size. In this case determining an accurate population of SOE employees was not possible. A 2020 report by Trade & Industrial Policy Strategies (TIPS) indicated that SOEs employ 175 000 direct employees (Makgetla, 2020). However, this study is targeted to employees who are at a decision-making level which is not possible to further deduce. In the absence of an accurate population size, other methods of sample size which does not require population size was used

A method is recommended a simple research model with normal data distribution, a sample size of 100 to 200 respondents is sufficient while a complex model with non-normal data distribution, a sample size of over 200 respondents is recommended (Rahman, 2023)

Challenges, such as time constraints, budget and other resource constraints may result in inadequate sample size (Bartlett et al., 2001). As such this research did experience challenges in achieving the desired sample size. Bartlett et al. (2001) has emphasised the need to explain the reasons and the implications on results. The desired sample size was not achieved in this study, however similar studies which were published in rated journals also presented similar sample size and the results were deemed sufficient. For example, Ferraris et al. (2019) had 88 usable responses in their study on big data analytics capabilities and knowledge management: impact on firm performance. Hair Jr et al. (2010) have discussed the potential challenges of having a small sample size such as the data not having enough statistical power to show significance. This is something that will be paid attention to in the analysis.

4.5. Data gathering process

Before the sample was sent out for data collection, it was tested by 5 people who tested for errors and basic understanding of the survey. The main purpose of the pilot was to verify if the questions are perceived as intended (Karunarathna et al., 2024). Feedback given was to put definitions for BDAC personnel and managers as well as DBAC projects. Feedback was also given that I should give examples of cutting-edge technology in one of the questions. The rest of the feedback was consistency in the Likert scale and semantics which was fixed accordingly.

The survey-questionnaire was shared with my network to reach employees who work for SOEs. The survey was also be posted on LinkedIn with a request for those who work for State Owned Enterprises to participate and others to share. The data was collected over a period of 6 weeks and during the 6 weeks follow ups and reminders were sent to the participants. Requests were also made to some participants, for them to share with their colleagues and others in their network that work for SOEs. The data gathering resulted in a total of 97 respondents of the 97 respondents 9 do not work for SOEs. This resulted in a total of 83 usable responses. All questions were made compulsory to submit the survey, so all surveys received were complete.

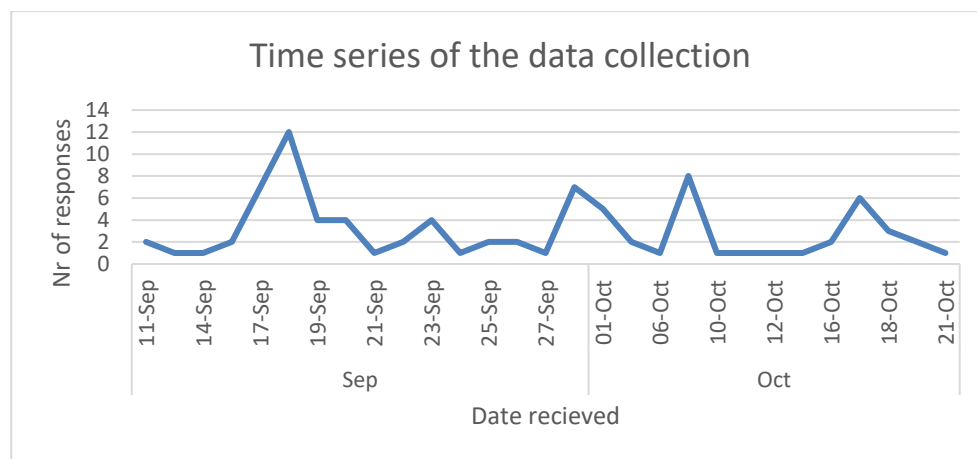


Figure 2:Data collection time series graph.

4.6. Analysis approach

4.6.1. Data cleaning and editing

The data will first need to be checked for validity and remove disqualifying data sets. This was done to ensure that the respondents are part of the target population and to remove those who are not. The first was to remove those who responded ‘No’ to the question, “Do you work for an SOE”. There were 9 people who responded no. This reduced the sample from 97 to 88. The study is targeted at employees at management level and those who are specialists in their field and have decision making power. Although this question was not asked explicitly the demographic data was used to remove those who may not fit this population, like interns and those who did not have an undergraduate degree as a minimum qualification, as well as those who had less than 2 years working experience. Although there was one respondent who had less than 2 years working experience that was kept in the sample, the reason being was that they had a Doctoral qualification and the functional area in the business is Information and Communication Technology and is in middle

management. The assumption was therefore made that the person has the necessary understanding to contribute to the study. The final sample size available for analysis is 82.

4.6.2. Data coding

The data was then be coded to convert to numeric values based on the Likert scale. This is done to ensure that the data can be analysed using a statistical analysis software, IBM SPSS Statistics. The demographic questions and the questions testing the constructs were all coded. The survey questions to test the constructs were asked from a positive standpoint; therefore, all the questions are coded in the same direction, the Likert scale was coded as follows.

Table 1: Likert scale coding

Likert	Code
Strongly disagree	1
Disagree	2
Somewhat disagree	3
Neutral	4
Somewhat agree	5
Agree	6
Strongly agree	7

4.6.3. Descriptive statistics analysis

The data was first be analysed for descriptive statistics. This first looked at the number of respondents, before and after data verification for completeness. The data was then be analysed for demographics such as level in the organisation, gender, years of experience and the type of industry.

The sample statistics was be analysed for general statistical characteristics, the mean and standard deviation, and the distribution of the data. The confidence interval used for the analysis is a 95% confidence interval. This is a middle ground of the recommended confidence interval range (Wegner, 2012).

4.6.3. Testing of the hypotheses.

The statistical analysis to test the hypothesis and the assumption of the statistical test is done on the SPSS statistical software. The confidence level that was used for the test was a 95% confidence level as it is the middle ground (Wegner, 2012).

Hypothesis 1

The first hypothesis which is that BDAC has a positive impact on service innovation is using data that is collected for the constructs in interval data, the averages of each construct according to the reliability components is used.

The constructs BDAC is not measured directly in the factors identified through the EFA. Structural equation modelling (SEM) was therefore the appropriate statistical test to test the relationship between the latent variable BDAC and service innovation (Hair et al., 2014). The SEM is generally suited for a small sample size (Hair et al., 2014), however the SEM results revealed an unidentified model. Although SEM is suitable for small sample sizes, Hair et al. (2014) has recommended that researchers should use caution as the guideline of five samples per parameter recommended by Barclay et al. (1995) does not take into account other factors such as model complexity, reliability and number of indicators. The SEM was used to test the relationship between the latent variable BDAC and service innovation. Amos29 which is an SPSS add on was used for this analysis. This was done by first creating the path model in Amos, and creating a constraint in the model before analysing (Hair et al., 2014)

The Pearson's correlation was also used to first test the individual relationships of the subconstructs to service innovation. The Pearson's correlation test measures the linear relationship between two continuous variables. To test for linearity a scatter plot of the independent and the dependant variable was done and visually inspected for linearity (Wegner, 2012). Scatter plots are effective in getting an indication of the relationship visually and to complement the statistical analysis (Hair Jr et al., 2010). While Pearson's correlation assumes that the data is normally distributed, it can still be used if the data is approximately normal. Since the normality test was not passed by some of the variables, Spearman's rho Correlation was used as an additional test. Spearman's rho is suitable for data used because the data did not completely pass the normality test. Spearman's rho is less sensitive to outliers compared to Pearson's correlation because it uses ranks instead of raw data values.

Hypothesis 2

The Linear Regression analysis is used to test the comparative impact of the BDAC constructs in service innovation and to test the hypothesis that the Human Skills BDAC, BDAC_HUMS has the biggest impact on service innovation. The data for this construct is the same data as the previous test which is interval continuous data using the averages of the constructs.

Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables (Hair Jr et al., 2010). It estimates the coefficients of the linear equation, involving one or more independent variables, that best predict the value of the dependent variable. This allows to quantify the impact of each independent variable on the dependent variable, which is why this test is suitable to test the second hypothesis. Linear regression has a few assumptions which are tested as part of the regression analysis. The assumption that will be tested are, linearity, independence, homoscedasticity, and normality of residuals (Hair Jr et al., 2010).

Hypothesis 3

The third hypothesis is that institutional pressure has a moderating impact on the relationship between BDAC and Service Innovation. To test this hypothesis a moderated regression was used.

The data was prepared by centre-ring the independent variables and the moderating variables. Centre-ring is done to reduce multicollinearity, which may be introduced by interaction variable and to improve the interpretation of the regression co-efficient. Centre-ring was done by subtracting the mean from all the BDAC construct values and subtracting the mean from all the Institutional Pressure constructs values. Interaction terms were prepared by multiplying the centred independent variable with the centred moderating variable (Boduszek, n.d.). The linear regression was then conducted on the relationship between the centred interaction variables to Service Innovation. All the assumptions of a linear regression were also tested.

4.7. Reliability and validity analysis

A number of questions, between six to nine were asked for each construct that will be tested in the study. Reliability tests were conducted using the Cronbach's Alpha to test the reliability of the data. The Cronbach's Alpha value that is acceptable to

confirm reliability is 0,7 (Hair et al., 2014;Shrestha, 2021). This test is a quality control measure to ensure that the questions asked in the survey were reliable to test the construct.

Factor analysis is done to give the researcher more consolidated constructs that form logical subsets (Shrestha, 2021). Exploratory Factor Analysis is used for developing a new survey while Confirmatory Factor Analysis is used for surveys that have been adapted from other researchers (Shrestha, 2021). Although for this study the survey questions were adapted from other authors, EFA instead of a CFA due to the small sample size of this study. The EFA was be done for the three subconstructs of BDAC and for service innovation and institutional pressure. The EFA is conducted using the Kaiser-Meyer-Olkin Measure (KMO). The KMO ranging between 0.8 to 1.0 are an indication of a sampled that has adequate validity (Shrestha, 2021), while KMO values between 0.7 to 0.79 are considered the middle range bit acceptable between 0.6 to 0.69 are mediocre (Shrestha, 2021).

4.8. Ethical Considerations

Ethical clearance for this study was approved at the Gordon Institute of Business Science's Ethical Clearance Committee on the 2nd of September 2024. The survey questions and the methodology of the study was presented. Ethical consideration is important as survey was administered electronically and to ensure that it was administered ethically. Use of online survey introduces some ethical issues such as anonymity and potential confidentiality, offering of rewards (Roberts & Allen, 2015)

The introductory comments stated that the survey is voluntary, and that withdrawal is permissible at any point during the survey. Confidentiality was also expressed and that the research is only used for academic purposes. Effort was made to ensure anonymity but not requesting any personal information, IP addresses were also not collected. Additionally, the characteristics, size as organisation size and industry of the SOE that the respondents worked for were not asked as these characteristics can be used to deduce the SOE. Personal demographic questions that would not add value to the study were not asked such as sex, race, income bracket. The survey was crafted on google forms and a link was shared to collect responses. Data storage for the survey responses was stored in the google drive account. The data collected will be stored for a minimum of 10 years after submitting the research.

4.9. Limitations

The research method being non-probability and purposive introduces a possibility of bias. Snowballing was also used to get access to more people in the population. Bias can be introduced with these sampling methods. (Wegner, 2012). The respondents due to their institutional contexts when the respondents are concentrated in a few public enterprises while in others give a few or no responses. An effort was made through the distribution of the survey to reach as many SOEs as possible and to limit the concentration in a few SOEs.

The sample may be a limitation for this study as there was less than the target sample size achieved. This may affect the results of the analysis by not providing statistical power to make the results significant (Hair Jr et al., 2010). Quantitative methods may face challenges related to unexpected variances and limited investigative depth, making them less flexible in exploring complex issues. (Karunaratna et al., 2024)

5. Results

5.1. Introduction

The purpose of this section is to test the hypotheses formulated in chapter three using the analysis methods discussed in chapter four. This section presents the data collected as specified in chapter four, and the analysis of the data. It starts off with the descriptive statistics of the sample collected to give a better understanding of who is the sample through the analysis of the demographics and the descriptive statistics of the constructs that will be analysed in this chapter. It is then followed by the reliability and the validity analysis to ensure that the questions are a good representation of the constructs being tested and that the questions are grouped correctly. Lastly the chapter will give an analysis of testing the hypotheses to answer the research questions.

The editing of the data that was collected and will be analysed in this chapter, is presented in the table below. The responses that were received were 97 responses, however only 83 responses could be used for the analysis. This results in 86% of the data being usable.

Table 2: Breakdown of data editing.

Breakdown of data editing	Nr of responses	%
Total responses received	97	100%
Removed- not working for SOE	9	9%
Removed- education level	2	2%
Removed- management level	2	2%
Removed- years of experience	1	1%
Usable sample size	83	86%

5.2. Descriptive results and analysis

5.2.1. Demographic descriptive analysis

The descriptive statistics are done to check the representativeness of the sample and ensure that the sample is not bias to a certain demographic. The type of data collected for the demographics is categorical data for functional area, in some cases, ordinal data for years of experience, education level and management level. This data was analysed on Microsoft Excel and presented in the appropriate graphs.

Working experience of the sample was an important data to collect as this may affect the respondents understanding of big data analytics and its application in the organisation. The results of working experience are shown in the pie chart below and show that more than 75% of the respondents have more than 10 years of working experience, and 30% have more than 20 years working experience. Only 1%, 1 respondent who has less than 2 years' experience was kept in the sample. This is because of the level of education, Doctoral Degree and their management level, middle management as well as their functional area in the business ICT, gives an indication that they have a good understanding of the survey questions.

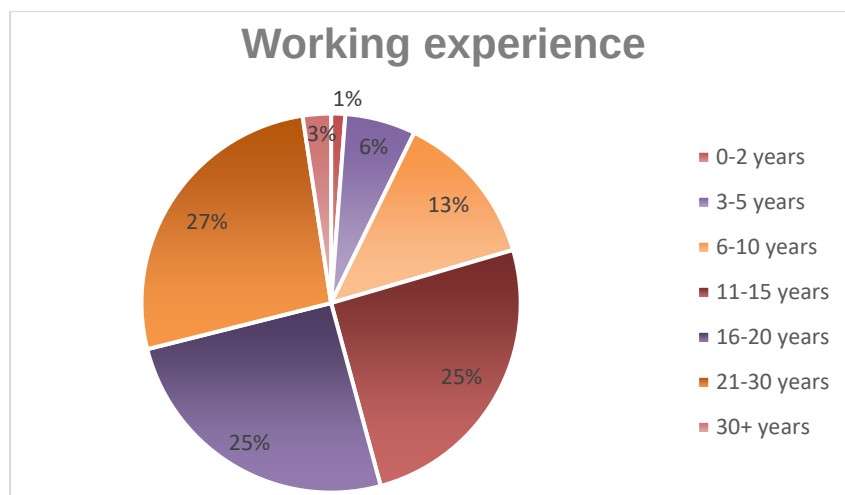


Figure 3: Working experience of the sample

The age group of the respondents was tested and is presented in the bar graph below. Majority of the respondents 51, more than 50% are between the ages of 36 and 45. Respondents were not excluded from the sample because of age, hence only one respondent was between the ages of 18-25 yrs.

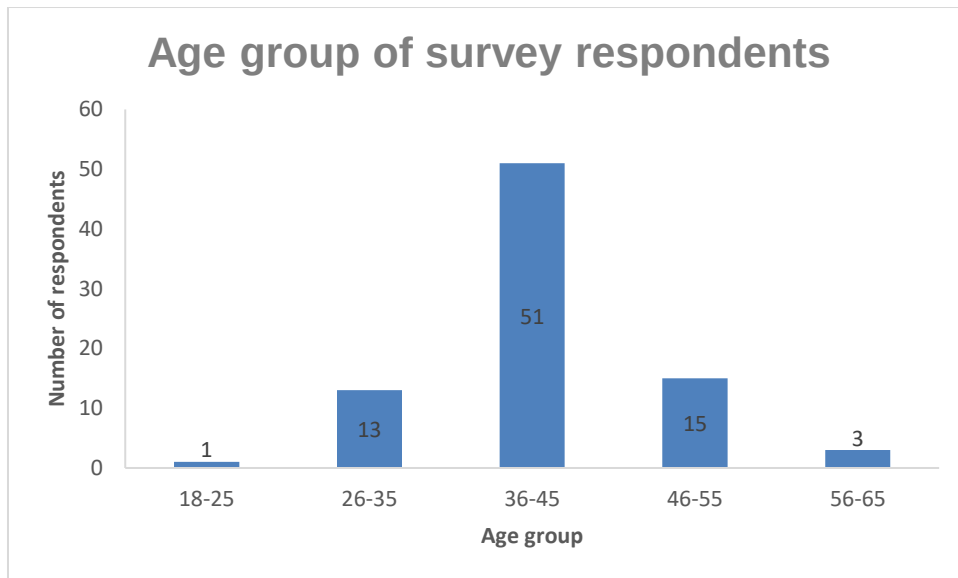


Figure 4: Age group of the sample

The level of education was considered an important element to test in the sample. The results are presented in a pie graph below. Majority of the respondents have a post-graduate degree, 49%, and respondents with a master's degree make up 30% of the sample, undergraduates are 16% of the sample and doctoral degree only 5% of the sample.

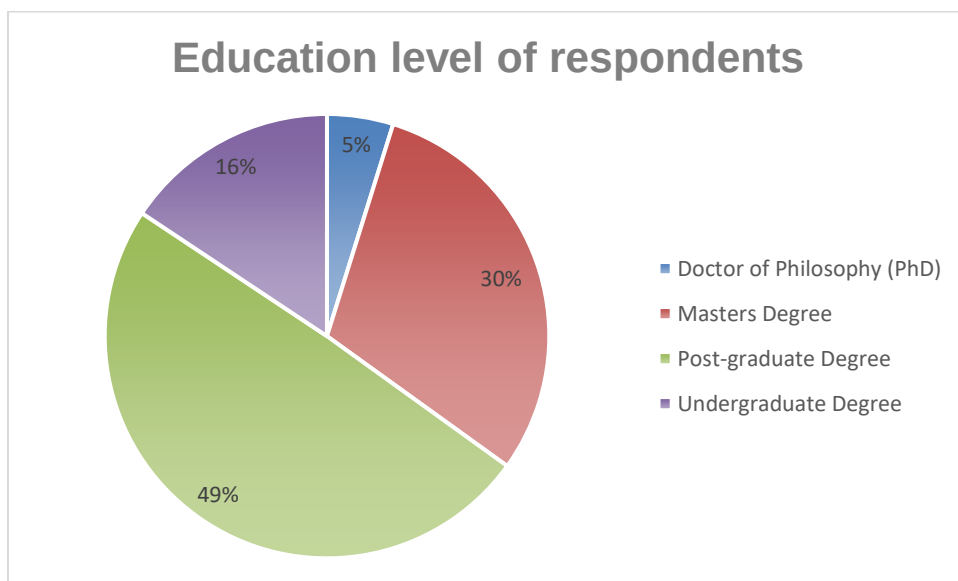


Figure 5: Education level of the sample

Management level was also an important factor to test as it gives an indication on the level on influence and decision-making power in an organisation. The results of the management level of the sample are presented in the bar graph below. The results show that the management level is mostly evenly distributed across all the levels, with the exception of executive level which was much less than the other

levels.

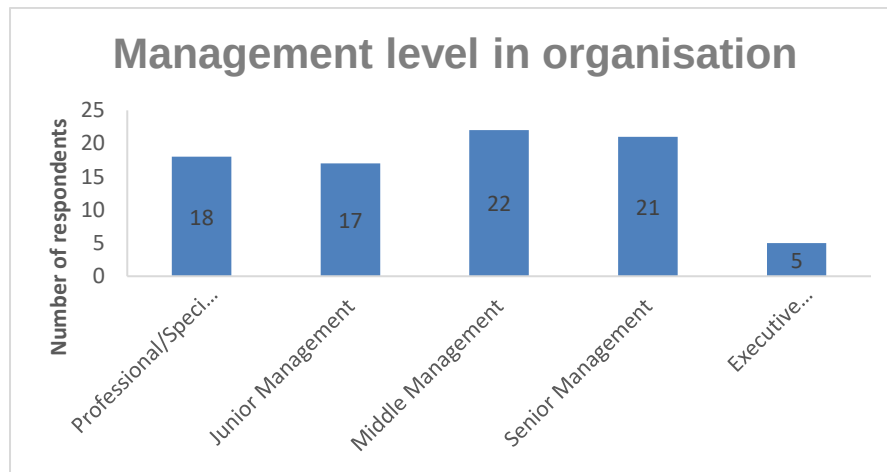


Figure 6: Management level of the sample.

BDA infrastructures capabilities can improve communication amongst the various functions in the organisation, enabling them to collaborate and finding innovative solutions (Aljumah et al., 2021). It is very important that BDA is embraced by the entire organization (Aljumah et al., 2021). The functional area was therefore an important factor to analyse to ensure a good representation of most functions within the organisation and that their experience and perspective on the constructs are considered. The results of this factor are displayed in the table below. The top three functions represented, Engineering, Maintenance and Projects, Information and Communication Technology and Strategy and Innovation, are all closely represented at 20%, 18% and 17% respectively.

Table 3: Functional area of respondents

Functional area in business	Nr of respondents	% of respondents
Engineering/Maintenance/Projects	17	20%
Information and Communication technology	15	18%
Strategy and Innovation	14	17%
Operations	11	13%
Financial Management	8	10%
Human Resource Management	5	6%
Legal, Risk and Compliance/ SHERQ	6	7%
Other	7	8%

5.2.2. Descriptive statistics of the constructs

The survey questions to evaluate the constructs was presented in a Likert scale which was later coded as explained in chapter four. The coded data is interval data which was analysed on SPSS using the descriptive statistics function. The purpose

was to get a fair understanding of what the data on the constructs is looking like. The table below presents the findings of the sample statistics. The mean of all the constructs is between 4,25 and 5,12 and the standard deviation between 0,89 and 1,52.

Table 4: Descriptive Statistics of the sample

	N	Minimum	Maximum	Sum	Mean	Std. Deviation	Variance
BDAC TAN	83	2,00	7,00	385,80	4,6482	1,25040	1,563
BDAC INT	83	1,00	7,00	386,32	4,6545	1,21507	1,476
BDAC HUMS	83	1,00	7,00	353,44	4,2583	1,52515	2,326
SI	83	1,00	7,00	352,53	4,2473	1,33147	1,773
IP	83	2,75	6,63	425,68	5,1287	,89159	,795
Valid N (listwise)	83						

5.2.3. Test for Normality

To conduct statistical tests, Pearsons's correlation and linear regression analysis, there is an assumption of normality of the data. The constructs were therefore tested for normality using the Shapiro-Wilk test. The results for the normality test are shown on the table below. The p value, for significance was observed to be greater than 0,05 for three of the constructs, BDAC TAN, BDAC INT and SI. This means that these constructs failed the test for normality. The rest of the constructs, BDAC HUMS and IP displayed P values less than 0,05 which means that the data is normally distributed.

Table 5: Tests of Normality

	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BDAC TAN	,092	83	,082	,972	83	,071
BDAC INT	,095	83	,060	,973	83	,074
BDAC HUMS	,094	83	,066	,965	83	,022
SI	,065	83	,200*	,985	83	,445
IP	,129	83	,002	,951	83	,003

To further investigate normality, histograms and Q-Q plots were analysed for all the constructs. The figure below shows the histograms and Q-Q plots. Although some of the tests for normality failed the graphs do not show a large deviation from normality. Considerations to remove outliers were decided against because of the already small sample size and the non-severity of outliers as observed in the graphs below. It was

also noted that removing the outliers may result in the removal of important observations for the analysis.

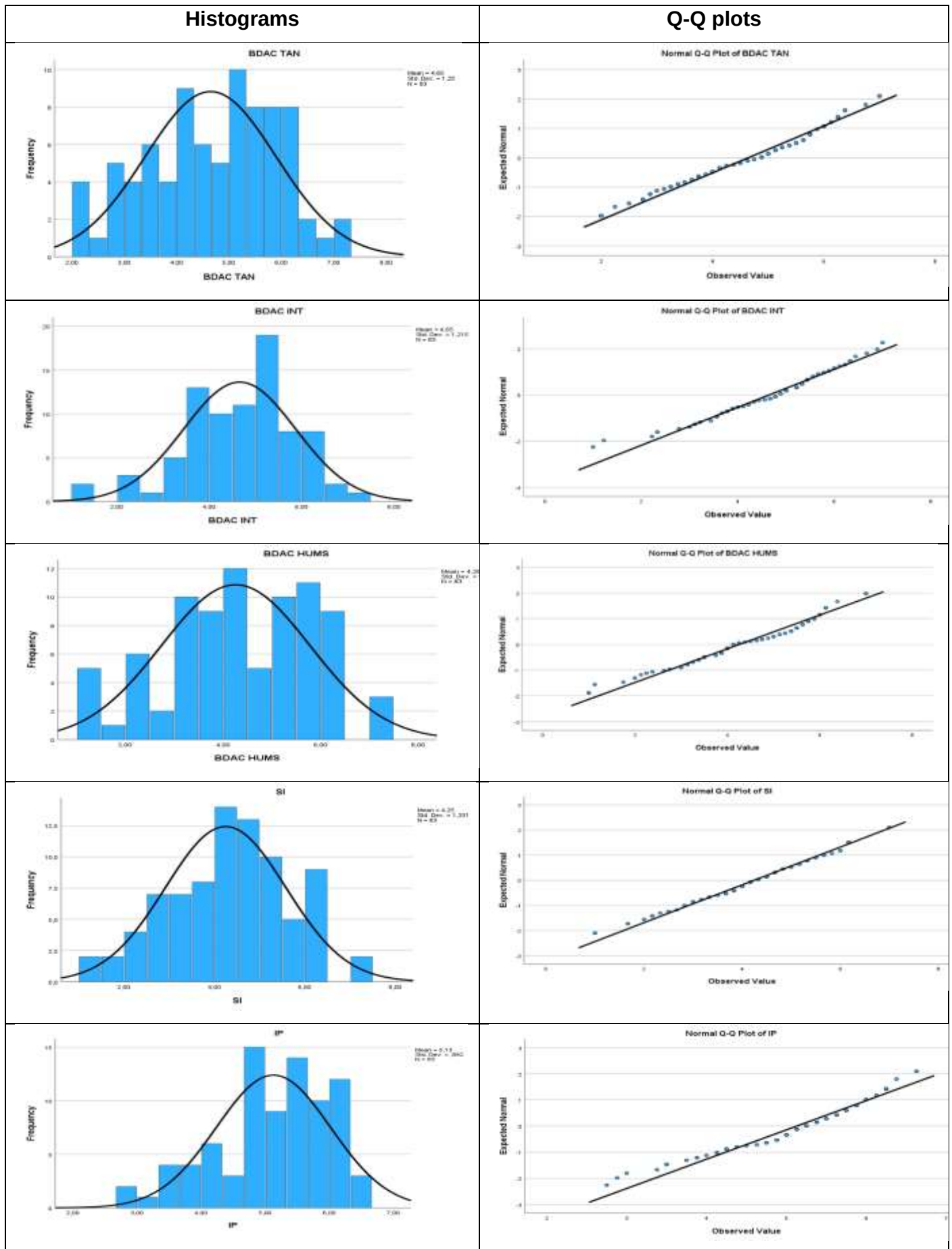


Figure 7: Histograms and Q-Q plots of the main constructs.

5.3. Reliability of data

The reliability of the data collected is tested using the Cronbach's Alpha. The details of the Cronbach's Alpha test are provided in the Appendix C. The table below presents a summary of the results for each construct. All the constructs resulted in a Cronbach's Alpha greater than 0,7 (Hair et al., 2014; Shrestha, 2021) which can be accepted as the average variance is also greater than 0,5 (Hair et al., 2014). Therefore, there is an acceptable level of consistency and reliability in the questions to test the construct thus, no questions were removed from the data.

Table 6: Reliability results of main constructs

Constructs	Cronbach's Alpha
BDAC_TAN	0,860
BDAC_INT	0,899
BDAC_HUMS	0,954
SERV_INN	0,892
INS_PRE	0,797

5.4. Validity of data

Validity tests were done on the constructs being tested. The questions on all the constructs were adapted from existing literature and the validity should be tested using a Confirmation Factor Analysis (CFA). However due to the large sample size required for a CFA and the small sample that was collected in this study, validity will be tested using Exploratory Factor Analysis (EFA). The result of the validity will be presented below per construct.

5.4.1. BDAC TAN

The factor analysis results measured by the Kaiser-Meyer-Olkin Measure measured a result of 0,835 for BDAC TAN. The test also measured a significant p-value which is less than 0,05. This indicated that the questions are valid to measure the construct

Table 7: KMO and Bartlett's Test for Tangible BDAC

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,835
Bartlett's Test of Sphericity	Approx. Chi-Square	278,125
	df	28
	Sig.	<,001

The anti-image matrix was observed to have at least one relationship between two questions, greater than an output value of 0,3, therefore no questions were under consideration to be removed from the questions to measure the constructs. The results also identified two components in the Rotated Component Matrix which result in 64,92% of the variance. The Rotated Component Matrix was used because the Component Matrix components were not giving a clear and logical separation of the questions into the two groups. The results of the Component Matrix and the Rotated Component Matrix and how the questions are categorised into components is in APPENDIX D. The two sub-constructs questions were analysed and therefore re-named to BDAC_BD, which is the BDAC for the Big Data component and the second sub-construct was renamed as BDAC_CT which is the BDAC for the connectivity technology.

5.4.2. BDAC INT

The factor analysis results measured by the Kaiser-Meyer-Olkin Measure measured a result of 0,888 for BDAC INT. The test also measured a significant p-value which is less than 0,05. This indicated that the questions are valid to measure the construct.

Table 8: KMO and Bartlett's Test for Intangible BDAC

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,888
Bartlett's Test of Sphericity	Approx. Chi-Square	407,517
	df	36
	Sig.	<,001

The anti-image matrix was observed to have at least one relationship between two questions greater than an output value of 0,3, therefore no questions were under consideration to be removed from the questions to measure the constructs. The Component Matrix results revealed one component of the questions which results in 56,72% of the variance. This construct was therefore not broken down to sub constructs.

5.4.3. BDAC HUMS

The factor analysis results measured by the Kaiser-Meyer-Olkin Measure measured a result of 0,904 for BDAC HUMS. The test also measured a significant p-value which is less than 0,05. This indicated that the questions are valid to measure the construct.

Table 9: KMO and Bartlett's Test for Human Skills BDAC

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,904
Bartlett's Test of Sphericity	Approx. Chi-Square	684,235
	df	28
	Sig.	<,001

The anti-image matrix was observed to have at least one relationship between two questions, greater than an output value of 0,3, therefore no questions were under consideration to be removed from the questions to measure the constructs. The Component Matrix results revealed one component of the questions which resulted in 76,19% of the variance. This construct was therefore not broken down to sub constructs.

5.4.4. SERV INN

The factor analysis results measured by the Kaiser-Meyer-Olkin Measure measured a result of 0,825 for SERV INN. The test also measured a significant p-value which is less than 0,05. This indicated that the questions are valid to measure the construct.

Table 10: KMO and Bartlett's Test for Service Innovation

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,825
Bartlett's Test of Sphericity	Approx. Chi-Square	313,299
	df	15
	Sig.	<,001

The anti-image matrix was observed to have at least one relationship between two questions greater than an output value of 0,3, therefore no questions were under consideration to be removed from the questions to measure the constructs. The Component Matrix results revealed one component of the questions which resulted in 65,79 % of the variance. This construct was therefore not broken down to sub constructs.

5.4.5. INST PRE

The factor analysis results measured by the Kaiser-Meyer-Olkin Measure measured

a result of 0,699 for INST PRE. The test also measured a significant p-value which is less than 0,05. This indicated that the questions are valid to measure the construct.

Table 11: KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,699
Bartlett's Test of Sphericity	Approx. Chi-Square	304,460
	df	28
	Sig.	<,001

The anti-image matrix was observed to have at least one relationship between two questions greater than an output value of 0,3, therefore no questions were under consideration to be removed from the questions to measure the constructs. The Component Matrix results revealed three components of the questions which resulted in 74,60 % of the variance.

The results of the Component Matrix and how the questions are categorised into components is in APPENDIX C. The three sub-constructs questions were analysed and upon careful analysis it was noted that one of the questions was not a good fit for the component. A decision was taken to remove this question from the component. Although this question was a better fit with the Normative Pressure questions it was categorised with the Mimetic Pressure question. The three components were therefore re-named as follows. The first one as IP_CP, coercive pressure, the second one as IP_NP which is normative pressure and the last one as IP_MP which mimetic pressure.

5.5. Hypothesis Testing

To test the hypotheses, it is important to first test for normality of the data. Previously normality was tested with the main constructs. Post the data validity tests, new sub-constructs were formed. The table below shows the normality test of the constructs and the level they will be tested in the hypothesis, using the Shapiro Wilk test. The results show that there is normality in the data except for two constructs which is the BDAC_INT and SERV_INN. These results for normality test have an implication on the tests that can be used to test the hypothesis. The results for basic statistics and normality of the revised constructs are in APPENDIX B.

Table 12: Tests of Normality for all sub constructs.

	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BDAC_TAN_BD	,161	83	<,001	,923	83	<,001
BDAC_TAN_CT	,105	83	,025	,968	83	,035
BDAC_INT	,095	83	,060	,973	83	,074
BDAC_HUMS	,094	83	,066	,965	83	,022
SERV_INN	,065	83	,200*	,985	83	,441
IP_CP	,187	83	<,001	,844	83	<,001
IP_NP	,159	83	<,001	,935	83	<,001
IP_MP	,139	83	<,001	,936	83	<,001

5.5.1. Hypothesis 1

The first hypothesis is that BDAC has a positive impact on service innovation. In the previous sections of this chapter, we tested for validity of the survey questions in testing the constructs, which then resulted into a breakdown of the tangible BDAC construct to be broken down to BDAC_BD and BDAC_CT. The other two BDAC constructs remain at one component as BDAC_INT and BDAC_HUMS. To test if BDAC has a positive impact on service innovation a Pearson's correlation test was first used to test the individual BDAC subconstruct relationships to service innovation used. However due to the normality test not passing for two constructs an additional test for Spearman's rho Correlation was also used. Scatter plots were also used to get a visual analysis of the direction and the strength of the relationship. See APPENDIX E for scatter plots.

The results to the two tests, Pearsons Correlation and Spearman's rho Correlation, are summarised below. The results show that all the BDAC constructs are positively correlated to Service Innovation, and that this correlation is significant, p-value less than 0,05, for all the BDAC constructs. The strength of Pearson's correlation and the Spearman's rho coefficient are between 0,6 and 0,75. The strength of the relationship is therefore moderately high (Wegner, 2012).

Table 13: Pearsons Correlation and Spearman's rho Correlation results

	Pearsons Correlation		Spearman's rho Correlation	
	Correlation Coefficient	P-value	Correlation Coefficient	P-value
BDAC_TAN_BD	0,624	<,001	0,631	<,001
BDAC_TAN_CT	0,625	<,001	0,615	<,001
BDAC_INT	0,772	<,001	0,725	<,001
BDAC_HUMS	0.710	<,001	0,743	<,001

The next test used to test the first hypothesis was the SEM model to produce the relation between the latent independent variable BDAC buy testing the BDAC components. SEM generally works well with sample size caution is still to be taken as they may be other nuances (Hair et al., 2014). The SEM is also suitable for data that does not pass the normal distribution tests (Hair et al., 2014), which is the case with some of the constructs in this study. The results for the SEM gave an overall Chi-square of 4,689, Degrees of freedom of 5, Probability level of 0,455. The table below indicates the model fit summary. The probability level of 0,455 means that there is no significant value between the model and the predicted value. This means the value is a strong fit to predict the relationships between BDAC and service innovation. The Chi-square value is for the model high, however when comparing it to the degrees of freedom the CMIN/DF is 0,938 which indicates a good fit for the model. Additional model fit results are available in the APPENDIX E

Table 14: SEM model fit summary.

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	10	4,689	5	,455	,938
Saturated model	15	,000	0		
Independence model	5	271,512	10	,000	27,151

The results in the table below show the estimate for the paths, in the model. The results show that all the paths are strong and positive, as they are closer to 1 (Hair et al., 2014) and they are statistically significant. The main path which is the relationship between BDAC and service innovation is also positive estimate of 0,842. H_0 is rejected and the hypothesis, H_1 is accepted that BDAC has a positive impact on Service Innovation.

Table 15: Structured Equation Model path results

	Unstandardised Estimate	Standardised Estimate	S.E.	C.R.	Plabel
SERV_INN <---BDAC	1,241	0,842	0,176	7,042	***
BDAC_TAN_BD <---BDAC	1	0,691			
BDAC_TAN_CT <---BDAC	1,237	0,745	0,197	6,292	***
BDAC_INT <---BDAC	1,24	0,921	0,164	7,579	***
BDAC_HUMS<---BDAC	1,442	0,854	0,202	7,129	***

5.5.2. Hypothesis 2

To test the second hypothesis, which is, the impact of BDAC HUMS on service innovation is greater than the other BDAC constructs, BDAC_TAN_BD, BDAC_TAN_CT and BDAC_INT, a multiple regression will be used. The results of the multiple regression are summarised in the table below. The model summary shows a high R^2 of 0,652 which means that 65 % of the variance in service innovation is observed from the constructs tested.

Table 16: Linear Regression Model Summary, BDAC → Service Innovation.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,808 ^a	,652	,634	,80485	1,995

a. Predictors: (Constant), BDAC_HUMS, BDAC_TAN_BD, BDAC_TAN_CT, BDAC_INT

b. Dependent Variable: SERV_INN

The anova table also shows that the regression model is significant. Taking a closer look at the coefficients of the regression model in the next table we can see that all the coefficients are positive, showing a positive impact of BDAC on service innovation. In addition to the BDAC_INT has the largest coefficient at 0,429, the next largest is BDAC_HUMS at 0,198 and then BDAC_TAN_BD at 0,193 and then lastly BDAC_TAN_CT at 0,097. Lastly, some of the coefficients are not significant in predicting the model, have a p-value which is greater than 0,05. The significant coefficients in the regression model are the coefficients for Intangible BDAC, BDAC INT and Tangible Big Data, BDAC, BDAC_TAN_BD.

Table 17: Linear regression model, ANOVA, BDAC → Service Innovation

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	94,770	4	23,693	36,575	<,001 ^b
	Residual	50,528	78	,648		
	Total	145,298	82			

a. Dependent Variable: SERV_INN

b. Predictors: (Constant), BDAC_HUMS, BDAC_TAN_TECH, BDAC_TAN_CON, BDAC_INT

The model also evaluates the Collinearity of the data measuring the constructs. Based on the results, the tolerance is greater than 0.1 and the VIF is less than 10 and there is therefore no relationship between the independent constructs being tested in the regression model.

Table 18: Linear regression model results, Coefficients, BDAC → Service Innovation

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-,029	,396		-,073	,942		
	BDAC_TAN_BD	,197	,091	,193	2,172	,033	,565	1,771
	BDAC_TAN_CT	,086	,085	,097	1,010	,316	,481	2,077
	BDAC_INT	,470	,137	,429	3,434	<,001	,286	3,499
	BDAC_HUMS	,172	,099	,198	1,733	,087	,343	2,912

a. Dependent Variable: SERV_INN

The corresponding regression model is presented below which shows a much stronger positive dependence on intangible BDAC and a weak positive dependence on the tangible big data BDAC

$$Serv_{INN} = 0,193 (BDAC_{TAN_{BD}}) + 0,429(BDAC_{INT})$$

The regression model has therefore proven to accept the null hypothesis H_0 and reject the hypothesis, H_2 that the human skills BDAC has the highest impact on service innovation.

5.5.3. Hypothesis 3

The third hypothesis, that institutional pressure has a moderating effect of the relationship between BDAC and service innovation. To test this hypothesis a moderated regression analysis is done. The results of the moderated regression are on the following tables. The results show an R^2 of 0,73 which shows that 73% of the variance can be explained by the independent variables. The anova table also shows that the regression model is significant. The model coefficients for the regression model however show to not be significant.

Table 19: Moderated linear regression model summary.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,854 ^a	,730	,648	,78976	1,983

Table 20: Moderated linear regression model, ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	106,003	19	5,579	8,945	<,001
	Residual	39,295	63	,624		
	Total	145,298	82			

The results also show some multi-collinearity in some variable, as indicated by the low tolerance levels, less than 0.1 and high Variance Inflation Factors, greater than 10 for 3 of the interaction variables namely the BDAC_INT with CP, the BDAC_INT with MP and the BDAC_HUM with CP. These three variables were removed from the model and the model was re-run. The results did not show much difference as the individual interaction variables were still statistically insignificant.

There are possible reasons why the individual variables do not show statistical significance while the main regression model shows statistical significance. It could be that the sample size is too small for the complexity of the model, a total of 20 variables was being tested including the interaction variables. Another reason could be that there is multicollinearity amongst the variable, this was tested and the factors showing high VIF values were removed, and the variable significance did not change. Therefore, to simplify the model an approach was taken to test how each sub construct of BDAC interacts with each subconstruct of IP. For all the individual

models run there was a significant regression model. For the individual interaction variables, the result of the interactions is summarised in the table below.

Table 21: Summary of results for the moderated linear regression models.

Independent Variable (BDAC)	Moderating Variable (IP)	B	Significance
BDAC_TAN_BD	IP_CP	-0,108	0,167
BDAC_TAN_BD	IP_NP	0,221	0,04*
BDAC_TAN_BD	IP_MP	-0,026	0,752
BDAC_TAN_CT	IP_CP	-0,153	0,087
BDAC_TAN_CT	IP_NP	0,097	0,091
BDAC_TAN_CT	IP_MP	0,082	0,176
BDAC_INT	IP_CP	-0,53	0,346
BDAC_INT	IP_NP	0,069	0,327
BDAC_INT	IP_MP	0,072	0,361
BDA_HUMS	IP_CP	-0,095	0,067
BDA_HUMS	IP_NP	0,087	0,155
BDA_HUMS	IP_MP	0,121	0,049*

*p ≤ 0,05

From the table, only two interactions of the moderating variable with the independent variable and that is the moderating effect of Normative Pressure on BADC_TAN_BD and the moderating effect of Mimetic Pressure on BDAC_HUMS. The findings of the moderated regression therefore indicate the null hypothesis H_0 is accepted and the Hypothesis H_3 is reject as the H_3 stated that institutional pressure has a negative moderating effect while it was found the moderating effect is in fact positive.

The results of the moderated regression that was significant were run on ModGraph to further analyse the moderating effect of institutional pressure. The figure below is an illustration of the moderating effect of MP on BDAC_HUMS. The graph displays the different slopes of the SERV_INN as BDAC_HUMS changes for the low, medium, and high level of moderator, IP_MP. The slope of the graph increases with an increase in the level of IP_MP. This means that the higher the mimetic pressure, the higher stronger the relationship between the human skills BDAC and service innovation.

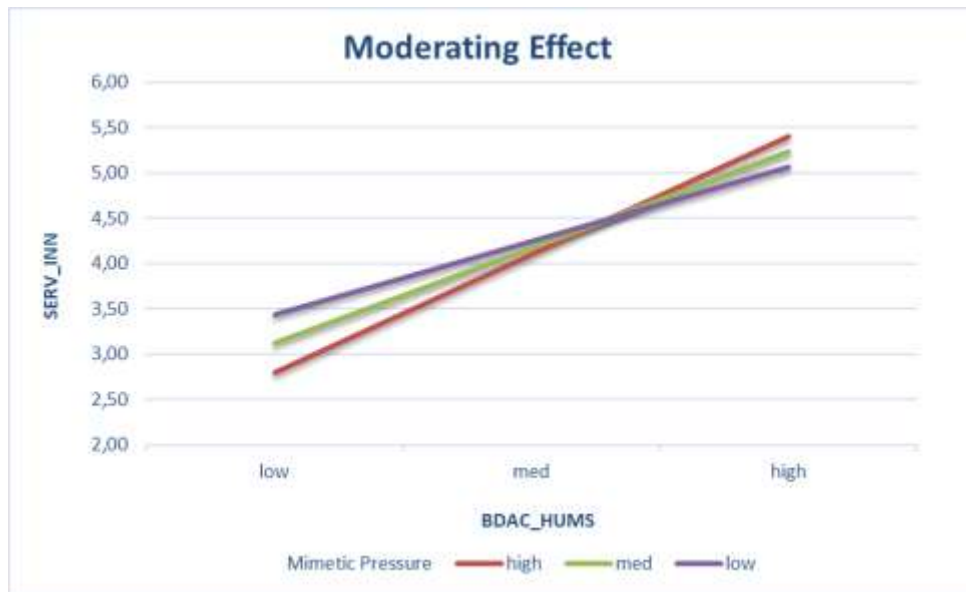


Figure 8: Moderation analysis graph for the interaction between BDAC_HUMS and Mimetic Pressure

The second moderating effect is the moderating effect of NP on the relationship between the BDAC_TAN_BD and SERV_INN. The slopes of the graph show an increase from low, medium to high. This means that the higher the normative pressure the stronger the relationship between BDAC_TAN_BD and SERV_INN

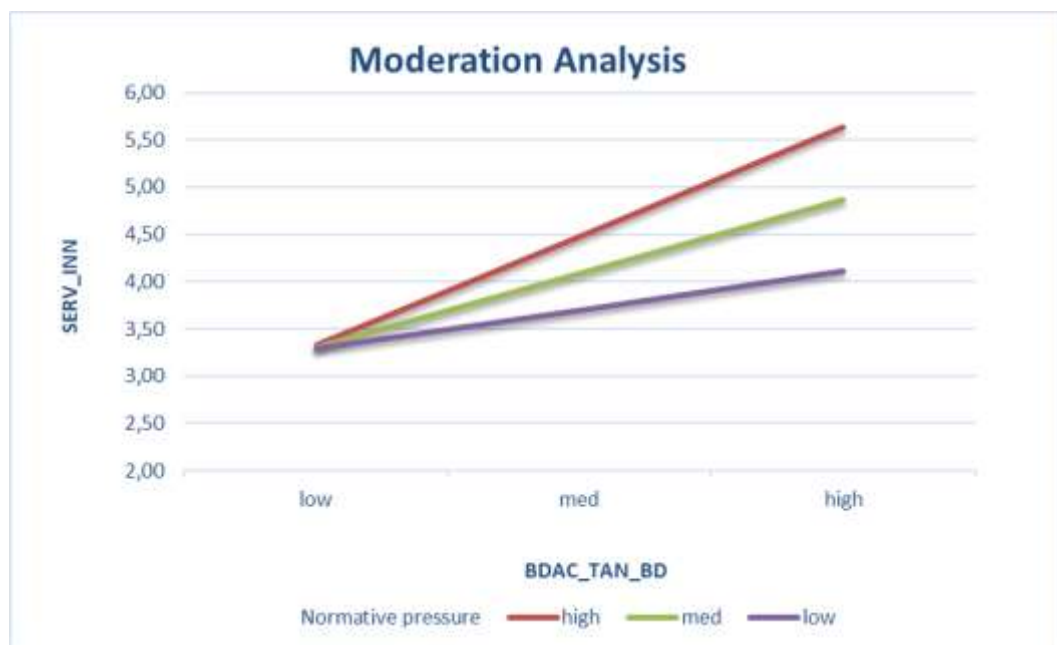


Figure 9: Moderation analysis of the interaction between BDAC_TAN_BD and IP_NP

5.6. Summary of results

The summary of the results are presented graphically in the diagram below showing all the significant relationships found in the study. The first hypothesis was accepted as it found that there is a positive impact on BDAC on service innovation. The second hypothesis was also rejected, which tested with a linear regression model shows that the impact of BDAC intangible capabilities is the strongest and is statistical significance moreover this capability is the only one that is not impacted by institutional pressure. Of the institutional pressure, it is found that coercive pressure has no impact on the relationship between BDAC and service innovation, it is therefore removed from the model

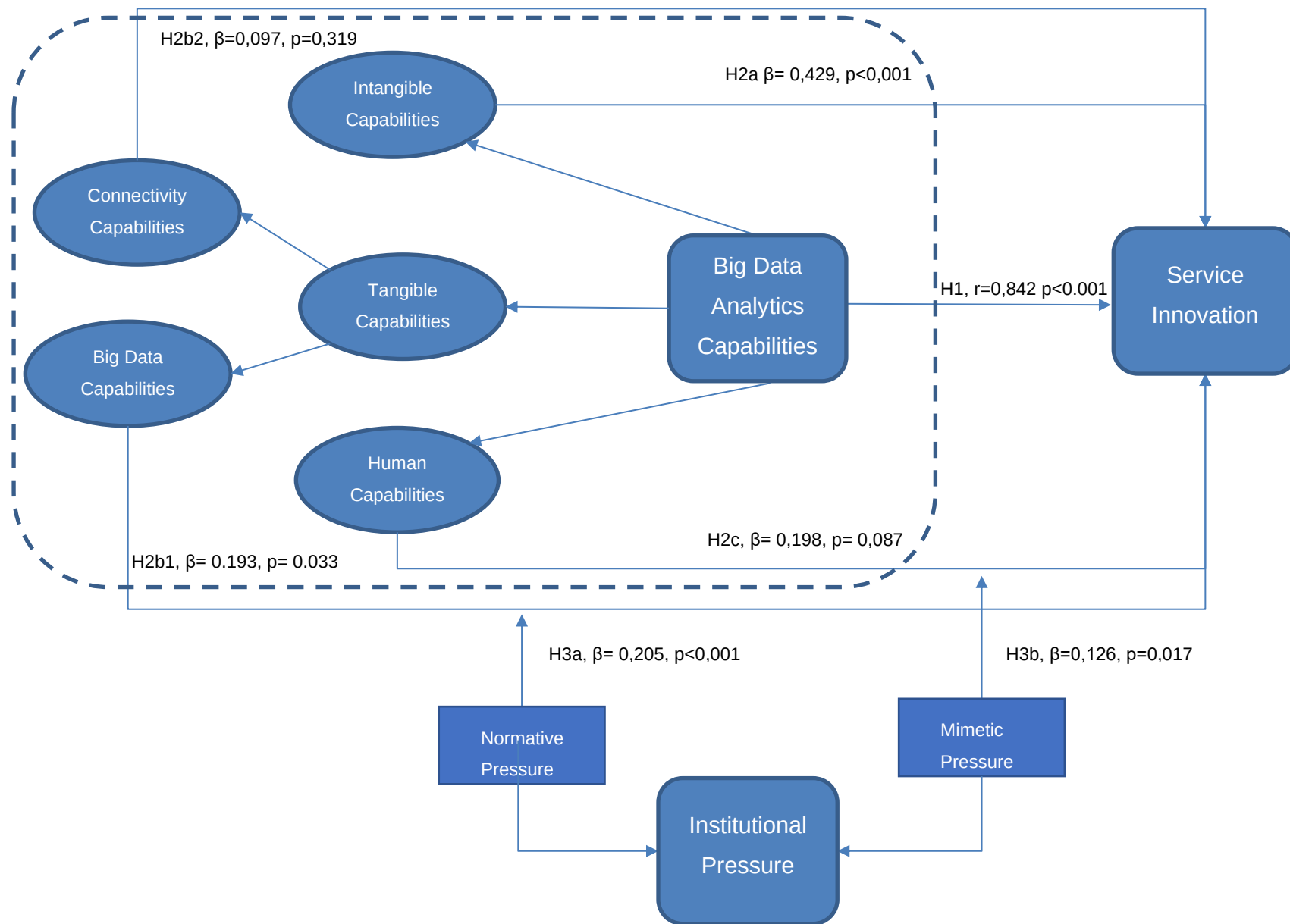


Figure 10: Model depicting the relationship between the constructs.

6. Discussion

6.1. Discussion of demographic analysis

The demographic analysis of the sample provides insights into the makeup of the sample and how they may represent the population. The approach of distributing the survey was purposive in that employees of SOEs were approached based on them working for schedule 2 SOEs and level in their organisation. Although not measured in this survey, for the sake of anonymity, an effort was made to reach only schedule 2 SOEs and as many as possible to avoid concentration in one or two SOEs. The study also did not limit the population to those who work in ICT as some of the studies in this field have done such as Wu et al. (2020) and Fosso Wamba et al. (2020) nor only leaders in ICT. The views of Mikalef et al. (2019) were taken in seeing BDAC as a management capability in which management works together with those who are specialist not only in ICT but other areas of the business where BDA is applied. The demographic questions selected were seen to have an impact on the respondent's exposure, experience and understanding of BDAC of lack-of thereof. This view, the importance of managerial and years' experience, was also held by Bahrami & Shokouhyar, (2022) in their study on the role of BDAC on firm performance. Some factors such as gender, race, income was considered to not be relevant demographics for this study.

None of the demographic analysis were assessed in relation with the constructs but were used to firstly get insights into the sample demographics and to identify if there was any bias in the sample, and secondly, to remove samples that do not represent the population. The sample demographic was well dispersed and a representation of the population.

6.1.1. Work Experience

With regards to work experience there was not specific target however many years' experience this study was targeting. However too few years of experience may indicate a lack of exposure to the constructs being tested. The results of the study showed that the respondents were quite seasoned in the work experience, more than 75% of the respondents have more than 10 years of working experience, and 30% have more than 20 years working experience. This is believed to be favourable to

the study as most of the respondents would have seen the transition into BDA and have the advantage of relative to the past. Respondents that have been working for too long however may also be stuck in their ways and not appreciative of the value of BDAC and innovation.

6.1.2. Age

Age was also another demographic that was considered as one which may need to be monitored for representation. The same type of bias presented in work experience may also be present in age. Majority of the respondents 51, more than 50% are between the ages of 36 and 45. This is a mix of younger Generation X and the older Millennials, generation Y. Generation Y is a generation that grew up in the technological driven area with access to instant information was growing (Mencel & Lester, 2014). They can therefore considered as more receptive of information technologies such as BDA. The sample is a good representation of workplace demographics as the age group 35-44 years has the highest labour participation rate, 79,5 % in 2024 in South Africa (SSA, 2024), therefore is likely to be the highest percentage. of the workforce

6.1.3. Education Level

Education level is considered to have an impact on the understanding on the constructs. For this reason, respondents who had lower than an undergraduate degree were removed from the sample. The remaining sample shows a high level of education amongst the respondents, 84% of sample have an education level higher than an undergraduate degree, from postgraduate up to doctoral level. This is higher than other similar studies that measured this demographic, (Bhatti et al., 2024), where only 40% of respondents had higher than undergraduate. Although they had also opened their sample to high school level graduates.

6.1.4. Management Level

The management level was considered in this study because of decision making power than is required for BDAC driven innovation. Empirical research also proven that appointment level has an impact on several factors such drive organisational performance, innovation, and knowledge management capacity (Kuo & Ye, 2010). The sample did not negate the importance of specialists in different functions who interact and use BDA in the day-to-day activities as well as the technical BDAC

capability which is a critical component of BDAC. The results of the sample demographics show a relatively even distribution of management level. Data collected from respondents who were interns was removed from the sample with the view that they did not have enough exposure to BDAC in their organisations. The well distributed sample across management level and specialist capability give a representative view of employee's perception of the constructs being tested.

6.1.5. Functional Area

With regards to the respondents' functional areas in the business, this was considered to be an important demographic to show representation of the application of BDAC from a more diverse view than from a one sided from of IT employees as some studies have done such as Bahrami and Shokouhyar (2022) who focused on IT managers and Executives only. Kuo and Ye (2010) provide empirical evidence in their study that IT applicability and knowledge management capacity is not a function of workplace designation. The top four functions that the respondents represent in the sample was Engineering/Maintenance/Projects, 20%, Information and Communication Technology, 18%, Strategy and Innovation, 17%, and Operations, 13%.

6.2. Sample statistics

Analysis into the basic statistics of the survey questions at a construct level, see APPENDIC B. The results presented the mean, the standard deviation as well as the minimum and maximum response of each of the constructs, The mean of all the constructs is between 4,25 and 5,12 and the standard deviation between 0,89 and 1,52. The standard deviation of greater than one shows that there is variability in the responses which will allow for testing of relationships.

The test for normality in the constructs revealed that two of the constructs did not pass the normality test. Further analysis through histogram and Q-Q plots revealed that there was no major skewness of the sample. As such tests that require normality can still be performed.

6.3. Hypothesis results analysis

The primary objective of the study was to determine the impact of BDAC on service innovation in SOEs. It was also to understand which components of BDAC has the most impact in driving service innovation in SOEs and lastly to determine what is the effect of institutional pressures on this relationship. The previous chapter under each hypothesis, presented the results and the discussion of those finding will follow per the three hypotheses.

6.3.1. Hypothesis 1

The test for the first hypothesis revealed that the H_0 was rejected and the H_1 was accepted. This hypothesis being tested

H_1 : BDAC have positive impact on Service innovation.

The BDAC was first tested through four sub-constructs using Pearson's correlation and Spearman's rho correlation, testing tangible big data, tangible connectivity technology, intangible, and human skills. All the sub-constructs were found to have a positive and significant relationship with Service Innovation, with two tests used Pearsons's correlation and Spearman's rho correlation. The co-efficient for both tests and for all BDAC sub -constructs was high between 0,63 and 0,74 signifying a strong relationship (Hair Jr et al., 2010). The correlation tests are testing the individual relationships not the ideal method as this does not take into account the varying weights if the subconstructs on the latent variable. SEM will be used to further analyse the latent variable BDAC measured through the subconstructs.

The relationship between BDAC and service innovation was further tested through the analysis of the observed variable. This was tested using the SEM, the results correspond with the results of the individual correlations between the subconstructs of BDAC and service innovation and show that there is a positive and direct impact of BDAC on service innovation. The path estimates for BDAC and service innovation was measured as 0,84. This presents a strong positive relationship.

The ubiquity of BD has resulted in a growth in the research into understanding how big data can create value for organisations. This has led to a lot of research into

BDAC through the RBV to enable organisations to have a competitive advantage. BDA enhances decision making capabilities which are critical for firms to innovate effectively. These capabilities help organizations stay agile by enabling speed of information required to make decisions and changes to processes and products based on insights derived from data. This adaptability is linked to both incremental and radical innovation, as firms can more accurately predict market needs and adjust their strategies (Mikalef et al., 2020). BDAC also facilitates business model innovation, enabling companies to rethink and redesign their value propositions, target markets, and revenue streams. This capability is particularly valuable in data-driven industries, where data insights allow companies to continuously refine and expand their business models in alignment with evolving customer demands and market trends (Ciampi et al., 2021).

These studies suggest that BDAC, when managed as a strategic resource in alignment with RBV, provides a significant advantage in achieving sustainable and dynamic innovation outcomes. For organizations, investing in BDAC can foster a culture of data-driven decision-making that supports long-term growth and adaptability in an ever-changing business environment.

The findings of this hypothesis in this study are consistent with previous research on innovation at a broader level. Mikalef et al. (2019) found that BDAC has a positive and significant relation to incremental and radical innovation only when mediated by dynamic capabilities. Theirs is different to this research because they found that the direct relationship between BDAC and innovation (both radical and incremental) to be insignificant, while this study found the direct relationship to be significant. Additionally, the strength of the relationship, the extent to which the BDAC explain the variation in innovation was, 36% and 37% respectively, which is considered to be moderate (Hair Jr et al., 2010). Ciampi et al. (2021) in their study tested the direct relationship of BDAC on business model innovation and found that there is a positive statistically significant relationship, the strength of the relationship was found to be relatively strong 0,636 but the only 40% of the variation in business model innovation was explained by BDAC, R^2 of 0,4. The strength of the relationship shows similar strength to that found in this study

In another study on the impact of BDAC on supply chain resilience, it was found that

BDAC has a positive and significant relationship with innovative capabilities, while it also mediated the relationship between BDAC and supply chain resilience (Bahrami & Shokouhyar, 2022). Another study shows a positive and significant impact, 0.56 coefficient of BDAC on supply chain innovation (Bhatti et al., 2024). Based on the above literature, there is sufficient evidence that BDAC has a positive impact on different types of innovation. The summary of the comparative studies is presented in the table below.

Table 22: Comparative findings of similar studies with significant relationships between BDAC and innovation

Authors	Relationship to	Direct or mediated	Significant	Co-efficient
(Ciampi et al., 2021)	Business Model Innovation	Direct	Significant	0,636
(Bhatti et al., 2024)	Supply Chain Innovation	Direct	Significant	0,56
(Yaşar et al., 2024)	Service Innovation	Direct	Significant	0,36
(Xiao et al., 2020)	Service Innovation	Direct	Significant	0,388
(Zondi, 2024) current study	Service Innovation	Direct	Significant	0,84

As discussed in the literature review there were limited studies that empirically tested the impact of BDAC and service innovation, one of those was a study by Xiao et al., (2020) which found that the human skills BDAC had a positive, co-efficient 0,388 and significant relationship with service innovation and tangible BDAC had a positive impact, co-efficient of 0,296, and significant relationship with Service Innovation. The study by Xiao et al. (2020) did not focus on the intangible BDAC which are a critical component to BDAC and lend to the RBV. Furthermore, this study Xiao et al. (2020) focuses on the mediating impact of dynamic capabilities like the work of Mikalef et al., (2020). The context of their study is a variety on companies in different industries in China. These results may not be generalised to the context of this study because China's economy is growing much faster than the South African economy and the study was not done exclusively to SOEs.

Another recent and study of the impact of BDAC on service innovation which was conducted in the hotel industry in turkey found a positive, co-efficient of 0,36, and significant relationship (Yaşar et al., 2024). The key difference in their study is that it measured individual employee behaviour in service innovation in the hotel industry.

Their application of service innovation was from the older perspectives which view service innovation as innovation in the service sector (Yaşar et al., 2024). Although service innovation can be applied in sectors providing goods or tangible products and providing typical services (Raddats et al., 2022; De Luca et al., 2021) The main difference of this study is that it looks at service innovation for the delivery of products and services.

This closed the gap on BDAC literature by focussing on a different context which is SOEs. It also adds to the literature of BDAC on service innovation as this literature is still very limited. The findings thus reveal that there is a place for BDAC in SOEs and that this can assist in driving the mandate of SOEs which may not always be driven by profits but also has socio-economic and service delivery component.

6.3.2. Hypothesis 2

The results for the second hypothesis show that the null hypothesis is accepted, and the hypothesis is rejected. The hypothesis being tested was.

H₂: The relationship between human skills and service innovation is stronger than the relationship between intangible and service innovation, and tangible and service innovation.

BDAC is driven by an interplay between the underlying components of BDAC, this hypothesis focussed on testing how the BDAC component contribute to service innovation. A linear regression analysis was used to test this hypothesis. The results show that human skills capabilities, BDAC_HUMS, has a lower coefficient than intangible capabilities, BDAC_INT, which has the largest coefficient at 0,429 the next largest is human skills capabilities at 0,198 and then tangible big data capabilities at 0,193 and then lastly tangible connectivity capabilities at 0,097. Human skills capability is also not statistically significant in the linear regression model in relation to the other variables. The intangible big data capabilities have the strongest and statistically significant impact on BDAC. Comparing these results from the results of the first hypothesis, it can also be concluded that the BDAC capabilities work better together, as they are tested in the SEM and all the paths were positive and significant, as compared to individually as tested in the linear regression model. The SEM results

also found that the intangible capabilities have the strongest impact on service innovation. Therefore, while the BDAC capabilities work together it can be concluded that tangible resources can go a long way on their own to drive service innovation.

RBV highlights those big data analytics is not just a technical endeavour. It requires the development and coordination of various non-technical resources to establish a BDAC (Mikalef et al., 2019a). As such a lot of research on BDAC draws from the RBV. This is important to know as practitioners invest in resources that will enable BDAC led innovation. Resource acquisition and retention, at the right capacity, is at the core of RBV (Yaşar et al., 2024) as it focusses on rare and inimitable resources.

Some research did not look at the different components of BDAC separately (Yaşar et al., 2024; Zheng et al., 2022) to understand how the different components contribute to BDAC. Yasmin et al. (2020)'s qualitative study investigated that relative importance of the BDAC components. Their study was based on the infrastructure, human skill, which is technical skills and management capabilities characterisation of BDAC. Amongst the three groups they found that the infrastructure BDAC ranked the highest, all in the top four ranking. Which means they have the highest level of importance. Within the human skills BDAC some were second ranked, those pertaining to standardisation of operations and processing with the ICT department, while the higher-level management human skills capabilities pertaining to alignment of BDA strategy to organisational strategy were ranked even less important (Yasmin et al., 2020). This finding indicates the perception that ICT as a support department, providing technology infrastructure as opposed to a strategic capability in the organisation. This study was conducted in Pakistan which is considered as a developing country (Yasmin et al., 2020) and this view may be different in more developed countries.

This then leads to the possibility that the relative importance of the components of BDAC are also contextually driven. For example, Mikalef et al. (2020) found some evidence of different contribution of the components of BDAC. They found that, when it comes to radical process innovation capabilities, the resources that play a key role are different, strong managerial capabilities play a bigger role. This suggests that while strong managerial direction may not be necessary for incremental improvements, it is crucial for achieving radical process innovation. Similarly, they

observed that the more intangible aspects of BDA, such as a data-driven culture and organizational learning, particularly for firms in the service industry and in relation to incremental process innovation capabilities (Mikalef et al., 2020). The results of this research were contradictory to this view which was derived from the findings from other authors as discussed above but this can also be synthesised, because of the role of management in organisations in driving data driven culture. Which would put the human skills, inclusive of management as having more impact in using BDA to drive data driven service innovation

This research has found the intangible BDAC to have the largest impact on service innovation. In the research that has focused on the BDAC components, rarely has there been a light shown on the intangible BDAC capabilities. Some authors have not even included it in their assessment, and some using the infrastructure, human resources, and management (Yasmin et al., 2020; Rialti et al., 2019; Bag et al., 2021; Aljumah et al., 2021) which does not have a deep focus on the intangible capabilities, have not even given much consideration to it. However, some authors have recognised the importance of the intangible capabilities as having a vital role in driving successful BDA projects (Fosso Wamba et al., 2020; Upadhyay & Kumar, 2020).

Given the unique context of this study and the findings of the importance of the intangible BDAC in driving service innovation, this study is adding to the limited theory and is giving opportunity for further investigation on how the BDAC components vary with context. This research is also adding to the dynamic and contextual nature of BDAC as the results on the BDAC components are rarely consistent and therefore highlighting the need for more research in different contexts to understand the nuances of BDAC.

For practitioners in SOEs, this will mean the approach of implementing BDAC may be different where they might focus on building a data-driven culture before investing in expensive infrastructure. Managers should drive a cultural shift to promote the use of Big Data Analytics (BDA) and intelligence, integrating evidence-based decision-making into the fundamental operations of the business (Mikalef & Krogh, 2020).

6.3.3. Hypothesis 3

The results analysed for third hypothesis found that the hypothesis is rejected. The hypothesis being evaluated was

H3: Institutional pressure has a negative moderating impact on the relationship between BDAC and service innovation.

The findings are that there is a positive moderating effect of normative pressure on the relationship between tangible big data capabilities and service innovation and that there is positive moderating effect of mimetic pressure on the relationship between human skills big data capabilities and service innovation. The findings of the moderated regression therefore indicate the null hypothesis H_0 is accepted and the Hypothesis H_3 is rejected.

The moderating effect of mimetic pressure on the relationship between human skills BDAC and service innovation is more complex because the effect of a low mimetic pressure yields higher service innovation when the human skills BDAC is low verses when the human skills BDAC is high, the service innovation becomes lower. This is an interesting finding because at low human skills BDAC mimetic pressure has a positive moderating effect but at high human skills BDAC mimetic pressure has a negative moderating effect.

This could be an indication that when organisations are reacting under mimetic pressure the human skills resources that they may get to try and be competitive may actually have a more negatively impact on service innovation. When the mimetic pressure is low, the skills might not be there but the impact on service innovation is better than getting the wrong skills under pressure. However, when the high mimetic pressure is responded to by getting the right skills, this has a positive effect on service innovation. This means the leaders should not respond hastily to mimetic pressure and should take time to find the right skills as failure to do so could have a negative impact on the human skill BDAC, service innovation relationship. This is consistent with the argument by DiMaggio and Powell (1983) that organisations tend to mimic without the full understanding of technologies, citing that the uncertainty may leave organisations desperate to be remain successful.

With respect to the normative pressure on the tangible BDAC and service innovation

relationship, the impact is found to increase with an increase in normative pressure (Dubey et al., 2019b) argues that the behaviour of an organisation is driven more by the need for legitimacy and less by competition and desire for efficiency. This is an indication of the legitimacy that SOEs seek as they engage with their stakeholders in the business environment.

The theory of institutional pressure and BDAC and innovation, has not focused on its moderating effect. However, theory that looks at the impact of institutional pressure on BDAC can assist us in understanding how it can moderate the relationship between BDAC and service innovation. Of these studies, Bag et al. (2021) tested the impact of institutional pressure on BDAC. The study draws from institutional theory and resource-based view theory to describe how organizations arrange tangible capabilities and develop human skills to enhance technological support, thereby advancing sustainable manufacturing practices and circular economy capabilities. The findings were that there is a positive and significant impact from coercive on human skills, while there is no significant impact of normative pressures on tangible resources, and there is no significant impact of mimetic pressures on human skills (Bag et al., 2021). There are similar findings in this study, as it was found that normative pressure had a significant positive moderating effect on the relationship between tangible big data capabilities and service innovation. It also found that mimetic pressure had a significant and positive relationship effect on the relationship between human skills capabilities and service innovation. The difference however was identified in that coercive pressure did not show significant interaction with any of the BDAC components and service innovation relationship.

Similarly Dubey et al. (2019b) also tested the impact of IP on the different components of BDAC. Their findings were similar to the findings of this study on coercive pressure as they found no significant relationship between coercive pressure and BDAC. They found that institutional pressure (i.e., CP, NP, and MP) has a significant impact on tangible BDAC, and that NP and MP have significant effects on human skills capabilities, whereas CP does not. They attributed to this notion to that the skills necessary for BDAC may not be influenced by social pressures (Dubey et al., 2019b). This finding and view may be contextual as Bag et al. (2021)'s results were contradicting and they argued that in the South African context the BBBEE regulations has influenced organisations to put in place skills

development programmes which will increase their BBBEE score as required to do business with the state and other organisations. Their empirical findings have also found that this coercive pressure has an impact on the BDAC human skills in South African manufacturing companies. Contrary to this, this study has not found that coercive pressure has no influence on any of the BDAC, including human skills which means the pressure to comply with BBBEE is not based on regulatory requirements but based on the social pressure and the legitimacy required to do business with other businesses in South Africa.

The findings on the impact of institutional pressure on BDAC were again confirmed by Klein et al. (2023) who also found that coercive pressure has an impact on BDAC. They also found, contrary to Bag et al., (2021), that the relationship between coercive pressure and human BDAC skills was not significant

The findings of this study support the argument by Butzbach et al. (2022) which challenges perception that the state's control over SOEs is prevalent and presents a more nuanced view that SOEs may have interests independent of the state and can peruse institutional change to gain resources by leveraging other stakeholders. This is consistent with findings of this study on the positive moderating effect of mimetic pressure on human skills, which shows that SOE are influenced by their counterparts and competitors to employ human skills BDAC which will result in improved service innovation while on the other hand not so much influence by government regulations. This is evident in that coercive pressure does not have a moderating effect on the relationship between BDAC and service innovation. The positive moderating effect of mimetic pressure on the human skills BDAC and service innovation relationship is also an unexpected finding because of the less competitive market structure theorised for SOE, which we would expect are less prone to react to competitive pressure, however we have also seen in the moderating effect graph that this pressure can be detrimental if not applied cautiously.

This study provides a new dimension to the literature on BDAC and institutional pressure as it tests institutional pressure as a moderator, as opposed to the other studies discussed above which focus on the direct impact of institutional pressure on BDAC. It also provides a new finding which contradicts most of the research on the impact of institutional pressure, particularly coercive pressure which is related to

government regulations.

7. Conclusion

7.1. Summary of findings

The research aims to determine what the impact of BDAC is on service innovation in SOEs. This research will assist leaders in SOEs in their quest to invest in BDAC to improve their efficiency and performance through service innovation. The study aims to understand the impact of the individual components on BDAC. This will help managers in SOE understand how to apportion their available resources into building BDAC. The research will also uncover the role of institutional pressure in moderating the impact of BDAC driven innovation.

The findings to this research were that there is a positive impact of BDAC on service innovation. It also found that the BDAC factor that has the biggest and most significant impact on service innovation is the intangible capabilities. Lastly it found that the relationship between BDAC and service innovation is positively moderated by institutional pressure. This is seen when it comes to the relationship between tangible capabilities pertaining to big data on service innovation and normative pressure, and on the relationship between human skills capabilities on service innovation and mimetic pressure.

Looking at the findings holistically it is interesting to see that the most impactful BDAC component with is intangible BDAC is not impacted by the institutional pressure. This finding is positive and may be detrimental for SOEs because on the one hand if they get it right then the impact will not be interfered with by any institutional pressures. However, if they do not get it right that the impact is great on the ability to drive service innovation.

7.2. Implications of findings

These findings suggest that there is benefit for SOEs to invest in BDAC to drive their service innovation. It also suggests that having an innovative culture and an organisational learning culture should be a priority in building a BDAC capabilities. This means that managers should influence a cultural shift that will be conducive to the use of Big Data Analytics (BDA) and integrating evidence-based decision-making

into the fundamental operations of the business. As the presence of BDA alone may not directly lead service innovation, but the development of data driven culture and the value placed on information can encourage such outcomes (Mikalef & Krogstie, 2020). Given the high investment required for BDA infrastructure and human skills, organisations can make the mistake of spending money on this resource without working on the intangible capabilities. This may lead to incorrect conclusions that big data projects did not bring any value to the organisation.

The findings add to the contribution of literature of the impact of BDAC on service innovation. The limited research on the impact of BDAC and service innovation makes this research to be making significant contribution to BDAC and service innovation literature. It is also contributing significantly because it looks at service holistically as the delivery of new products and services (Troilo et al., 2017) which is the servitisation (Raddats et al., 2022). This approach of servitisation is becoming even more relevant with the rise of BDA, digitalisation, and the use of AI and opens up a new area of research in the future (Schymanietz et al., 2022).

Previous studies have studied institutional pressure's impact on BDAC (Dubey et al., 2019b; Bag et al., 2021). This study is the first to the best of the researcher's knowledge, that looks at the moderating effect of institutional pressure on the relationship between BDAC and service innovation. The findings are also different to previous studies, on the impact institutional pressure on BDAC particularly with regards to coercive pressure. This highlights the need for more research to understand its moderating effect.

This research is also adding to the dynamic and contextual nature of BDAC as the results on the BDAC components are rarely consistent and therefore highlighting the need for more research in different contexts to understand the nuances of BDAC.

7.3. Limitations

The sampling method that was used may cause a limitation to the results obtained. The research method used was non-probability purposive sampling. This sampling method may bring about biases. Bias can be introduced by the respondents due to their institutional contexts when the respondents are concentrated in a SOEs. The

research question did not ask which SOE a respondent works for, for the sake of anonymity and therefore the research could not pick up the representation of the sample in that aspect. An effort was made through the distribution of the survey to reach as many SOEs as possible. An effort was also made to limit penetration in a single SOE while trying to maximise the sample size, but this could not be fully controlled because of the use of snowballing.

The sample size collected did not meet the required sample size and that introduced some challenges in the analysis and the results by not providing sufficient statistical power to make the results significant (Hair Jr et al., 2010). Quantitative methods may face challenges related to unexpected variances and limited investigative depth, making them less flexible in exploring complex issue. (Karunaratna et al., 2024). This was seen mostly in testing of hypothesis as the moderating linear regression introduced a more complex model. Also contributing the sample size limitation was the available time frame to complete this study.

The research is cross-sectional and not longitudinal. While there is a rise in the availability of bid data and the use of BDA, the observed level of service innovation cannot be measured some time back before the rise of big data to support the results. The results therefore provide only a snapshot and can therefore not analyse the change that has taken place over time (Saunders & Lewis, 2018).

7.4. Future research recommendations

The dynamic capabilities view (DCV) of the BDAC is one that has been researched by some authors and the with that came the criticism of RBV as being static (Ciampi et al., 2021), this is important given the dynamic condition in which SOEs operate in. Even so in other contexts there is still a gap in understanding the impact of BDAC sensing capabilities (Ciampi et al., 2021). The ever-changing technology also implies that the capabilities for BDA cannot be looked at from a static and internal view which RBV does, but the sensing capabilities of the DCV become relevant in ensuring that the competitive advantage of BDAC that organisations hold remains relevant into the future. The DCV can capture the evolution of the BDAC resources over time (Yasmin et al., 2020). The recommendation, therefore, for future studies is for the dynamic capabilities view of BDAC and its impact on service innovation.

The results on the relative impact of the BDAC components has not been well researched and the findings have also not been consistent. There is an opportunity for researchers to develop a standard BDAC model that other researchers can use to build a theory on the BDAC components, ensuring a strong focus on all components, including intangible resources. Big data will continue to rise as the technology keeps improving. The BDAC research agenda will continue to remain relevant and therefore a BDAC model would assist researchers to have a framework on BDAC studies. This would in make the BDAC more comparable and assist in finding some common theories when it comes to the BDAC components.

There has not been a study found by this research that looks at the moderating role of institutional pressure on the relationship between BDAC and service innovation. While other studies have looked at the impact of institutional pressure on BDAC, it would be good to get more studies to contribute to literature in this regard. The importance of this impact is more relevant as the findings of the study contradicted the expectations based on literature, and findings from other authors as it pertained to coercive pressure. Expanding the research on institutional pressure will assist in confirming or disproving the perception of the role of coercive pressure particularly in SOEs. And will create more understanding in how to navigate the constraints of the regulatory environment when it comes to the use of data.

Another recommendation is to replicate the study to gain longitudinal results and with more time available to collect a larger sample size. The current study had a time limitation and therefore could not measure the change over time. The rise in big data is exponential and the impact of the rise would be beneficial in measuring how that impact on service innovation is changing over time. Additionally, as mentioned earlier that the BDAC is a dynamic capability, and the regulatory requirements and the institutional pressures are also not static. A longitudinal study will there be beneficial in measuring the changes in these relationships over time.

8. References

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APPENDIX A- Research questions

Qualifying question

Do you, or have you in the past two years, worked for a State-Owned Entity

Demographic questions

Age group

Functional Area in organisation

Nr Years of experience

Education Level

Management level

Research questions

Big Data Analytics Capabilities

Tangible Capabilities

1. We use advanced tools (like optimization/regression/simulation) for data analysis
2. We use data gathered from multiple sources or data analysis
3. We use data visualization techniques to assist decision makers in understanding complex information extracted from large data
4. Our dashboards display information, which is useful for carrying out necessary diagnosis
5. We have connected dashboard applications or information with the manager' communication devices
6. We have access to very large, unstructured, or fast-moving data for analysis
7. We integrate data from multiple sources into a data warehouse for easy access
8. We integrate external data with internal to facilitate analysis of business environment

Intangible Capabilities

9. Our 'big data analytics' projects are adequately funded
10. Our 'big data analytics' projects are given enough time to achieve their objectives
11. We base our decisions on data rather than on instinct
12. We are willing to override our own intuition when data contradict our viewpoints
13. We continuously coach our employees to make decisions based on data
14. We are able to acquire new and relevant knowledge
15. We have made concerted efforts for the exploitation of existing competencies and exploration of new knowledge
16. We are able to assimilate relevant knowledge
17. We are able to apply relevant knowledge

Management Capabilities

18. Our IT/Business Analytics managers can understand the business needs of other functional managers, suppliers, and customers to determine opportunities that big data might bring to our business
19. Our IT/Business Analytics managers can coordinate big data-related activities in ways that support other functional managers, suppliers, and customers
20. Our IT/Business Analytics managers can understand and evaluate the output extracted from big data
21. Our IT/Business Analytics managers can understand where to apply big data
22. Our 'big data analytics' staff has the right skills to accomplish their jobs successfully
23. Our 'big data analytics' staff is well trained
24. We provide big data analytics training to our own employees
25. Our 'big data analytics' staff has suitable education to fulfil their jobs

Service Innovation

1. We have improved and promoted existing services
2. We have repackaged and promoted existing services
3. We have extended and promoted existing service lines
4. We have introduced new services that competitors do not offer in the market
5. We have continuous improvement on service quality
6. We have adopted new technologies that enhance market offerings
7. We have enhanced services with cutting edge technology

Institutional pressure

1. The data protection law requires our organisation to use data safely.
2. The industry association requires us to use data within the boundary of regulatory norms.
3. The stakeholders of our organisation want us to exploit data to improve decision making without interfering into privacy of any individuals, which may attract defamation to the organisation.
4. The extent to which your organisation's suppliers use big data and predictive analytics for decision-making.
5. The extent to which your organisation's customers use big data and predictive analytics for decision-making.
6. The extent to which industry associations' promotion of big data and predictive analytics influences your organisation to use big data and predictive analytics for decision-making.
7. Our counterparts who have adopted big data and predictive analytics have greatly benefitted.
8. Our counterparts who have adopted big data and predictive analytics are favourably perceived by the others in the same industry.
8. Our counterparts who have adopted big data and predictive analytics are favourably perceived by their suppliers and customers

APPENDIX B: Descriptive statistics

	Tests of Normality					
	Kolmogorov-Smirnov ^a			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
BDAC_TAN_TECH	,161	83	<,001	,923	83	<,001
BDAC_TAN_CON	,105	83	,025	,968	83	,035
BDAC_INT	,095	83	,060	,973	83	,074
BDAC_HUMS	,094	83	,066	,965	83	,022
SERV_INN	,065	83	,200*	,985	83	,445
IP_CP	,187	83	<,001	,844	83	<,001
IP_NP	,159	83	<,001	,935	83	<,001
IP_MP	,139	83	<,001	,936	83	<,001

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

Descriptives				Statistic	Std. Error
BDAC_TAN_TECH	Mean			5,0060	,14336
	95% Confidence Interval for Mean	Lower Bound		4,7208	
		Upper Bound		5,2912	
	5% Trimmed Mean			5,0617	
	Median			5,2500	
	Variance			1,706	
	Std. Deviation			1,30605	
	Minimum			2,00	
	Maximum			7,00	
	Range			5,00	
	Interquartile Range			1,75	
	Skewness			-,757	,264
	Kurtosis			-,269	,523
BDAC_TAN_CON	Mean			4,2861	,16454
	95% Confidence Interval for Mean	Lower Bound		3,9588	
		Upper Bound		4,6135	
	5% Trimmed Mean			4,3069	
	Median			4,5000	
	Variance			2,247	
	Std. Deviation			1,49905	

	Minimum		1,00	
	Maximum		7,00	
	Range		6,00	
	Interquartile Range		2,50	
	Skewness		-,253	,264
	Kurtosis		-,870	,523
BDAC_INT	Mean		4,6545	,13337
	95% Confidence Interval for Mean	Lower Bound	4,3891	
		Upper Bound	4,9198	
	5% Trimmed Mean		4,7022	
	Median		4,8900	
	Variance		1,476	
	Std. Deviation		1,21507	
	Minimum		1,00	
	Maximum		7,00	
	Range		6,00	
	Interquartile Range		1,66	
	Skewness		-,606	,264
	Kurtosis		,485	,523
BDAC_HUMS	Mean		4,2583	,16741
	95% Confidence Interval for Mean	Lower Bound	3,9253	
		Upper Bound	4,5913	
	5% Trimmed Mean		4,2968	
	Median		4,1300	
	Variance		2,326	
	Std. Deviation		1,52515	
	Minimum		1,00	
	Maximum		7,00	
	Range		6,00	
	Interquartile Range		2,25	
	Skewness		-,373	,264
	Kurtosis		-,516	,523
SERV_INN	Mean		4,2470	,14611
	95% Confidence Interval for Mean	Lower Bound	3,9563	
		Upper Bound	4,5376	
	5% Trimmed Mean		4,2786	
	Median		4,3333	
	Variance		1,772	
	Std. Deviation		1,33114	
	Minimum		1,00	
	Maximum		7,00	

	Range		6,00	
	Interquartile Range		1,83	
	Skewness		-,259	,264
	Kurtosis		-,244	,523
IP_CP	Mean		5,8116	,11247
	95% Confidence Interval for Mean	Lower Bound	5,5878	
		Upper Bound	6,0353	
	5% Trimmed Mean		5,9087	
	Median		6,0000	
	Variance		1,050	
	Std. Deviation		1,02470	
	Minimum		1,00	
	Maximum		7,00	
	Range		6,00	
	Interquartile Range		1,34	
	Skewness		-1,890	,264
	Kurtosis		5,904	,523
IP_NP	Mean		4,5482	,15275
	95% Confidence Interval for Mean	Lower Bound	4,2443	
		Upper Bound	4,8521	
	5% Trimmed Mean		4,5535	
	Median		4,0000	
	Variance		1,937	
	Std. Deviation		1,39164	
	Minimum		2,00	
	Maximum		7,00	
	Range		5,00	
	Interquartile Range		2,00	
	Skewness		-,158	,264
	Kurtosis		-,676	,523
IP_MP	Mean		5,0723	,14035
	95% Confidence Interval for Mean	Lower Bound	4,7931	
		Upper Bound	5,3515	
	5% Trimmed Mean		5,1215	
	Median		5,0000	
	Variance		1,635	
	Std. Deviation		1,27865	
	Minimum		2,00	
	Maximum		7,00	
	Range		5,00	
	Interquartile Range		2,00	

Skewness	-,380	,264
Kurtosis	-,382	,523

APPENDIX C: Reliability analysis

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,957	0,958	25

BDAC TAN

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,860	0,861	8

BDAC INT

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,899	0,903	9

BDAC HUMS

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items

0,954	0,955	8
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Service Innovation (SI)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,892	0,894	6

Institutional Pressure (IP)

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
0,797	,805	8

Rotated Component Matrix^a

	Component	
	1	2
We use advanced tools (like optimization/regression/simulation) for data analysis.	,806	,151
We use data gathered from multiple sources for data analysis.	,737	,171

We use data visualization techniques to assist decision makers in understanding complex information extracted from large data.	,834	,250
Our dashboards display information, which is useful for carrying out necessary diagnosis.	,639	,307
We have connected dashboard applications or information with the manager's communication devices.	,192	,769
We have access to large, unstructured, or fast-moving data for analysis.	,078	,843
We integrate data from multiple sources into a data warehouse for easy access.	,486	,697
We integrate external data with internal to facilitate analysis of business environment.	,428	,662

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.^a

a. Rotation converged in 3 iterations.

Component Matrix^a

	Component		
	1	2	3
The data protection law requires our organization to use data safely.	,632	,622	,138

The industry association requires us to use data within the boundary of regulatory norms.	,569	,687	-,011
The stakeholders of our organization want us to exploit data to improve decision making without interfering into privacy of any individuals, which may attract defamation to the organization.	,625	,227	-,314
Our organization's suppliers use big data and predictive analytics for decision-making.	,695	-,360	-,428
Our organization's customers use big data and predictive analytics for decision-making.	,745	-,422	-,344
Industry associations' promotion of big data analytics influences your organization to use big data analytics for decision-making.	,292	-,290	,684
Our counterparts who have adopted big data analytics have greatly benefitted.	,772	-,204	,384
Our counterparts who have adopted big data analytics are favourably perceived by the others in the same industry	,833	-,144	,208

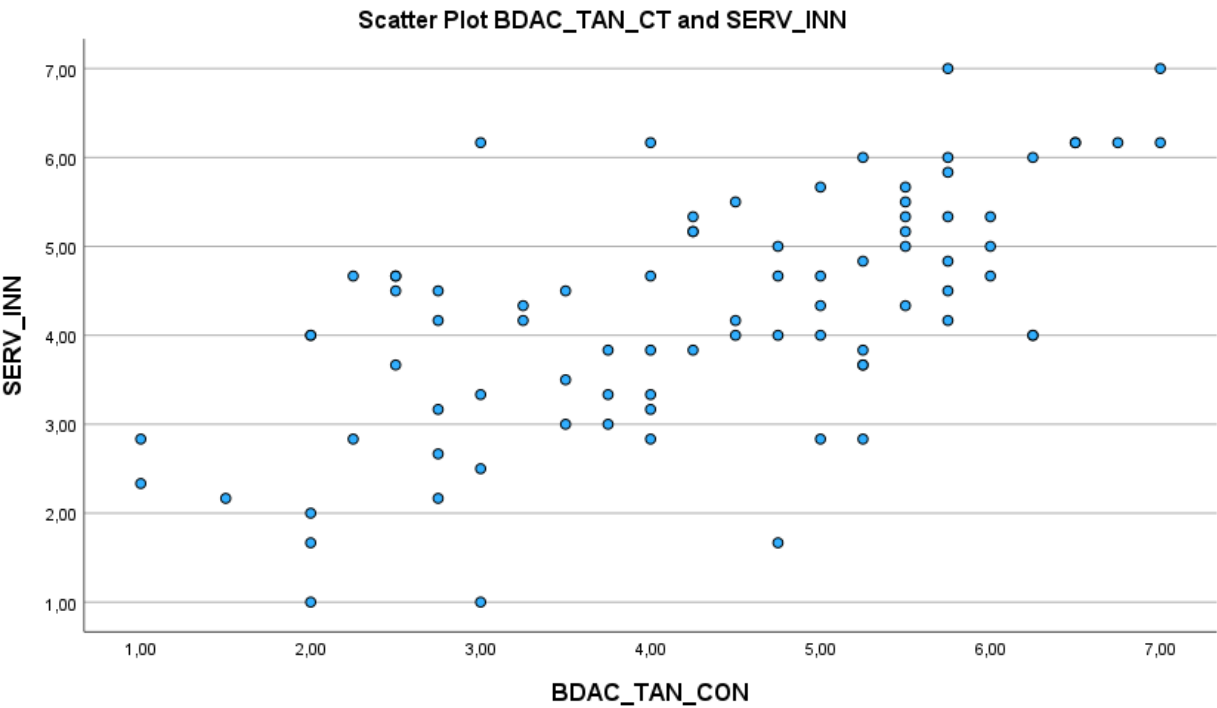
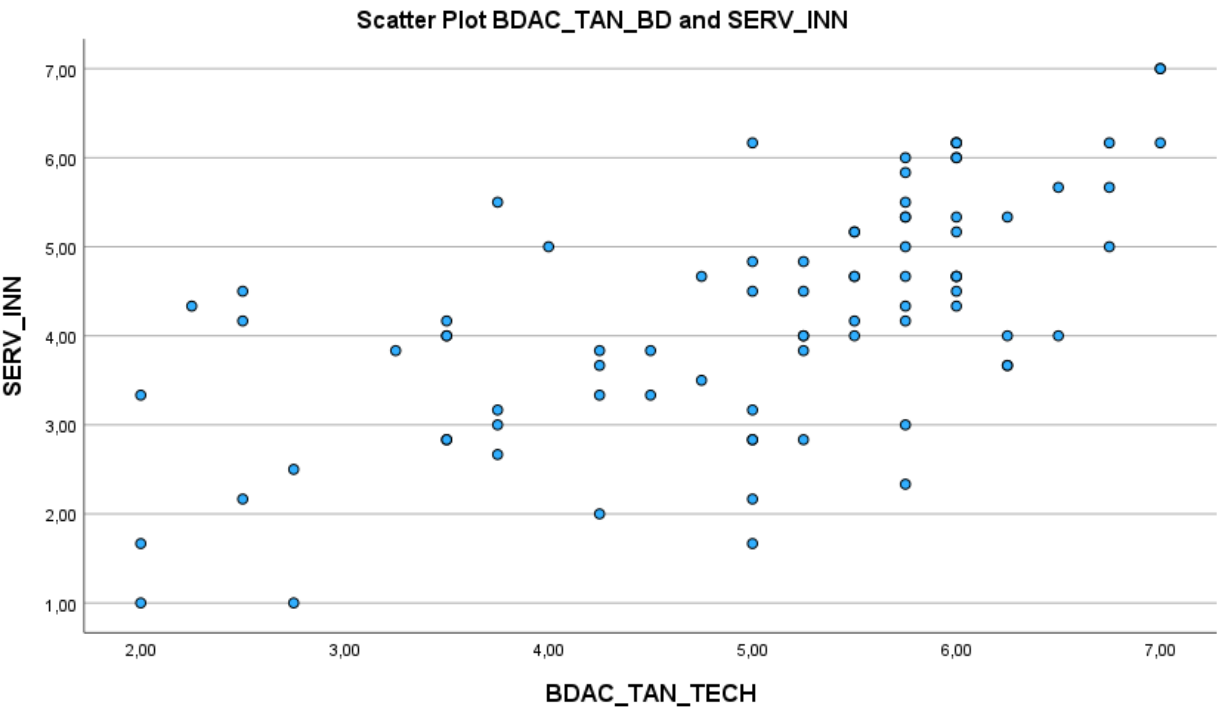
Extraction Method: Principal Component Analysis.

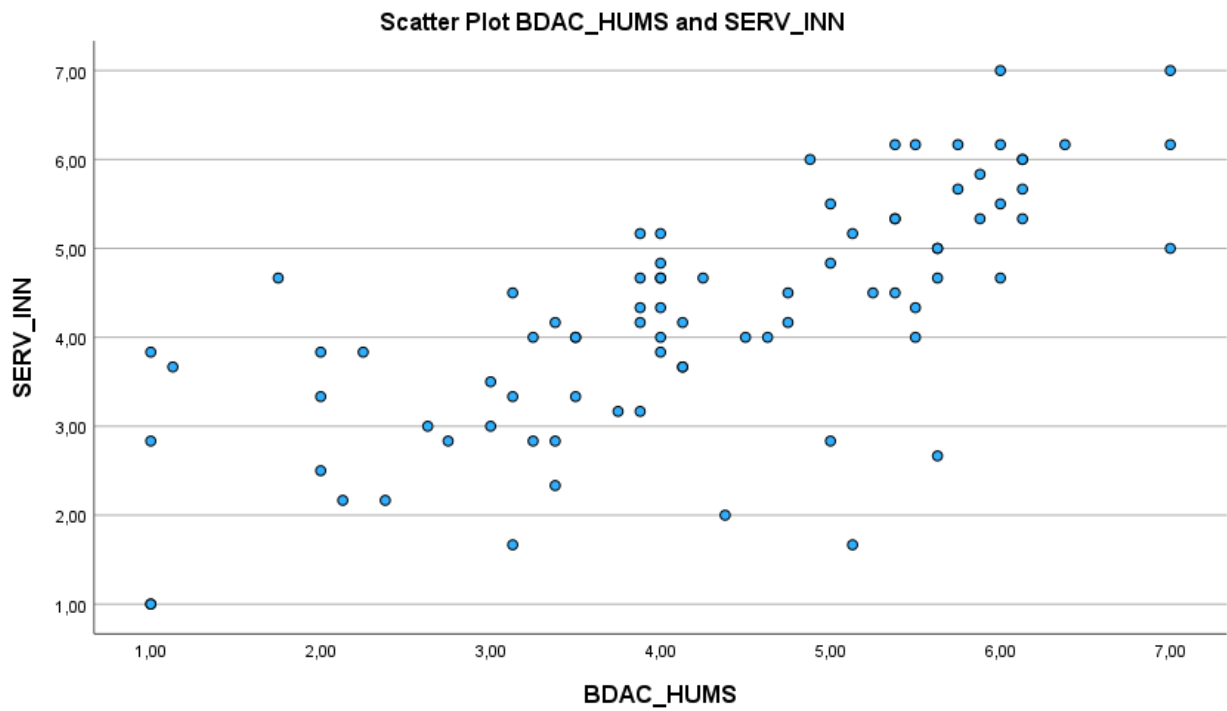
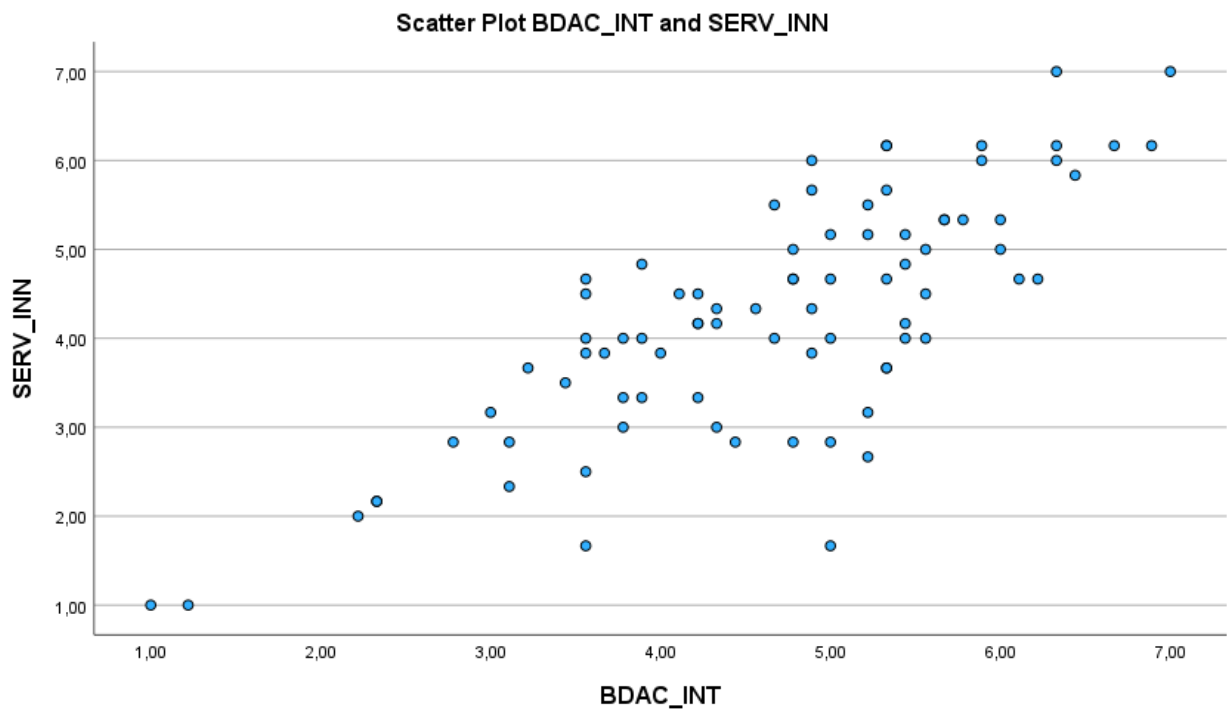
a. 3 components extracted.

APPENDIX D: Validity results

APPENDIX E: Hypothesis 1 tests results

Scatter plots





Correlations

Correlations

		BDAC_TAN_BD	SERV_INN
BDAC_TAN_BD	Pearson Correlation	1	,624**

SERV_INN	Sig. (2-tailed)		<,001
	N	83	83
	Pearson Correlation	,624**	1
	Sig. (2-tailed)	<,001	
	N	83	83

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

Correlations

		BDAC_TAN_CT	SERV_INN
BDAC_TAN_CT	Pearson Correlation	1	,625**
	Sig. (2-tailed)		<,001
	N	83	83
SERV_INN	Pearson Correlation	,625**	1
	Sig. (2-tailed)	<,001	
	N	83	83

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

Correlations

		BDAC_INT	SERV_INN
BDAC_INT	Pearson Correlation	1	,772**
	Sig. (2-tailed)		<,001
	N	83	83
SERV_INN	Pearson Correlation	,772**	1
	Sig. (2-tailed)	<,001	
	N	83	83

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

Correlations

		BDAC_HUMS	SERV_INN
BDAC_HUMS	Pearson Correlation	1	,710**
	Sig. (2-tailed)		<,001
	N	83	83
SERV_INN	Pearson Correlation	,710**	1
	Sig. (2-tailed)	<,001	
	N	83	83

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

Correlations

		BDAC_TAN_TECH	BDAC_TAN_CON	BDAC_INT	BDAC_HUMS	SERV_INN
Spearman's rho	BDAC_TAN_TECH	Correlation Coefficient	1,000	,627**	,629**	,593**
		Sig. (2-tailed)	.	<,001	<,001	<,001
		N	83	83	83	83
	BDAC_TAN_CON	Correlation Coefficient	,627**	1,000	,701**	,637**
		Sig. (2-tailed)	<,001	.	<,001	<,001
		N	83	83	83	83
	BDAC_INT	Correlation Coefficient	,629**	,701**	1,000	,808**
		Sig. (2-tailed)	<,001	<,001	.	<,001
		N	83	83	83	83
	BDAC_HUMS	Correlation Coefficient	,593**	,637**	,808**	1,000
		Sig. (2-tailed)	<,001	<,001	<,001	.
		N	83	83	83	83
	SERV_INN	Correlation Coefficient	,631**	,615**	,725**	,743**
		Sig. (2-tailed)	<,001	<,001	<,001	.
		N	83	83	83	83

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

SEM Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	10	4,689	5	,455	,938
Saturated model	15	,000	0		
Independence model	5	271,512	10	,000	27,151

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	,047	,977	,930	,326
Saturated model	,000	1,000		
Independence model	1,008	,362	,043	,242

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2	CFI
Default model	,983	,965	1,001	1,002	1,000
Saturated model	1,000		1,000		1,000
Independence model	,000	,000	,000	,000	,000

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	,500	,491	,500
Saturated model	,000	,000	,000
Independence model	1,000	,000	,000

NCP

Model	NCP	LO 90	HI 90
Default model	,000	,000	9,052
Saturated model	,000	,000	,000
Independence model	261,512	211,466	318,982

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	,057	,000	,000	,110
Saturated model	,000	,000	,000	,000
Independence model	3,311	3,189	2,579	3,890

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	,000	,000	,149	,569
Independence model	,565	,508	,624	,000

AIC

Model	AIC	BCC	BIC	CAIC
Default model	24,689	26,268	48,877	58,877
Saturated model	30,000	32,368	66,283	81,283
Independence model	281,512	282,301	293,606	298,606

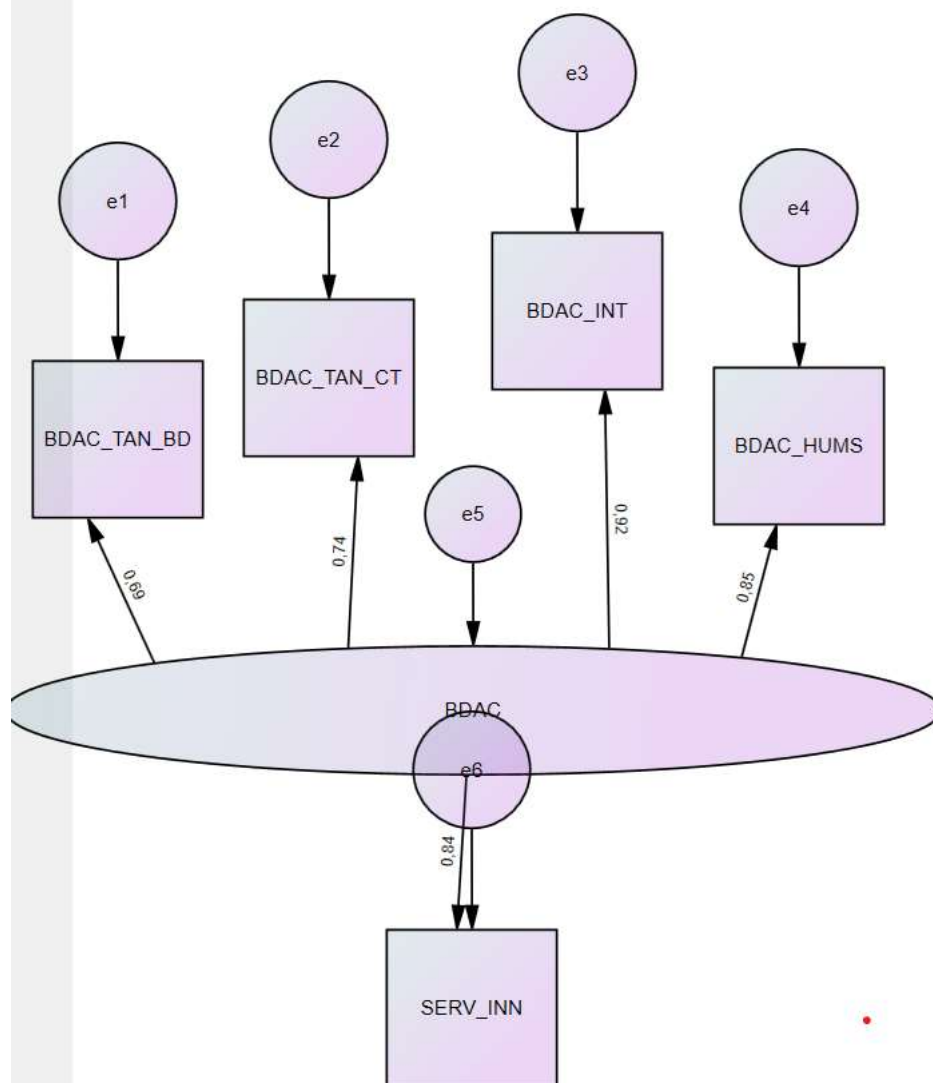
ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	,301	,305	,415	,320
Saturated model	,366	,366	,366	,395
Independence model	3,433	2,823	4,134	3,443

HOELTER

Model	HOELTER ,05	HOELTER ,01
Default model	194	264
Independence model	6	8

SEM Paths Model



SE

APPENDIX F: Hypothesis 2 tests

		Correlations				
		SERV_INN	Cent_BDAC_T AN_BD	Int_TANBD_CP	Int_TANBD_NP	Int_TANBD_MP
Pearson Correlation	SERV_INN	1,000	,623	-,195	,039	-,001
	Cent_BDAC_TAN_BD	,623	1,000	-,201	-,306	-,110
	Int_TANBD_CP	-,195	-,201	1,000	,312	,506
	Int_TANBD_NP	,039	-,306	,312	1,000	,573
	Int_TANBD_MP	-,001	-,110	,506	,573	1,000
Sig. (1-tailed)	SERV_INN	.	<,001	,039	,362	,496
	Cent_BDAC_TAN_BD	,000	.	,034	,002	,161
	Int_TANBD_CP	,039	,034	.	,002	,000
	Int_TANBD_NP	,362	,002	,002	.	,000
	Int_TANBD_MP	,496	,161	,000	,000	.
N	SERV_INN	83	83	83	83	83
	Cent_BDAC_TAN_BD	83	83	83	83	83
	Int_TANBD_CP	83	83	83	83	83
	Int_TANBD_NP	83	83	83	83	83
	Int_TANBD_MP	83	83	83	83	83

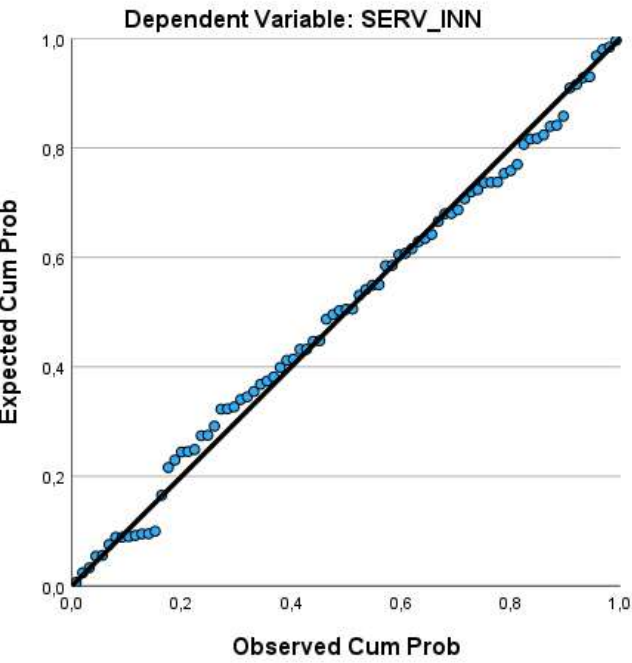
Collinearity Diagnostics ^a								
Model	Dimension	Eigenvalue	Condition Index	(Constant)	Variance Proportions			
					Cent_BDAC_T AN_BD	Int_TANBD_CP	Int_TANBD_NP	Int_TANBD_MP
1	1	2,287	1,000	,04	,02	,07	,07	,06
	2	1,002	1,511	,23	,62	,00	,00	,00
	3	,814	1,676	,47	,18	,04	,00	,18
	4	,608	1,939	,01	,02	,64	,29	,04
	5	,290	2,810	,25	,16	,25	,63	,71

a. Dependent Variable: SERV_INN

Residuals Statistics ^a					
	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	1,5950	6,2652	4,2470	,91025	83
Residual	-2,47008	2,65119	,00000	,97127	83
Std. Predicted Value	-2,913	2,217	,000	1,000	83
Std. Residual	-2,480	2,662	,000	,975	83

a. Dependent Variable: SERV_INN

Normal P-P Plot of Regression Standardized Residual



APPRNDIX G: Hypothesis 3 tests

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson
1	,737 ^a	,543	,526	,91641	1,936

a. Predictors: (Constant), Int_HUMS_MP, Cent_IP_MP, Cent_BDAC_HUMS

b. Dependent Variable: SERV_INN

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	74,859	3	24,953	27,985	<,001 ^b
	Residual	70,439	79	,892		
	Total	145,298	82			

a. Dependent Variable: SERV_INN

b. Predictors: (Constant), Int_TANBD_NP, Cent_IP_NP, Cent_BDAC_TAN_BD

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4,089	,113		36,137	<,001		
	Cent_BDAC_TAN_BD	,598	,091	,587	6,577	<,001	,772	1,296
	Cent_IP_NP	,279	,084	,291	3,332	,001	,802	1,247
	Int_TANBD_NP	,205	,059	,289	3,484	<,001	,892	1,122

a. Dependent Variable: SERV_INN

Descriptive Statistics

	Mean	Std. Deviation	N
SERV_INN	4,2470	1,33114	83
Cent_BDAC_HUM S	,0000	1,52515	83
Cent_IP_MP	,0000	1,27865	83
Int_HUMS_MP	,5867	2,08907	83

Correlations

		SERV_IN N	Cent_BDAC _HUMS	Cent_IP_ MP	Int_HUMS_ MP
Pearson Correlation	SERV_INN	1,000	,710	,146	-,056
	Cent_BDAC_HU MS	,710	1,000	,305	-,334
	Cent_IP_MP	,146	,305	1,000	-,204
	Int_HUMS_MP	-,056	-,334	-,204	1,000
Sig. (1-tailed)	SERV_INN	.	<,001	,094	,307
	Cent_BDAC_HU MS	,000	.	,003	,001
	Cent_IP_MP	,094	,003	.	,032
	Int_HUMS_MP	,307	,001	,032	.
N	SERV_INN	83	83	83	83
	Cent_BDAC_HU MS	83	83	83	83
	Cent_IP_MP	83	83	83	83
	Int_HUMS_MP	83	83	83	83