BUSINESS INTELLIGENCE CAPABILITY, ORGANISATIONAL CAPABILITY, COMPLEMENTARY RESOURCES AND PERFORMANCE OF FIRMS LISTED AT THE NAIROBI SECURITIES EXCHANGE

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A RESEARCH THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY IN BUSINESS ADMNISTRATION, FACULTY OF BUSINESS AND MANAGEMENT SCIENCES, DEPARTMENT OF MANAGEMENT SCIENCE AND PROJECT, UNVERSITY OF NAIROBI

2021

DECLARATION

I declare that this thesis is entirely my work and where there is contribution from other individuals, it has been duly acknowledged. To the best of my knowledge, this thesis has not been submitted to this or any other university for a ward of a degree.

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DEDICATION

This dissertation is dedicated to my wife Beatrice Mainga and my two daughters, Favor Gloria and Giana Sifa, who have been supportive for several years of challenging work. Your tenacity and moral support has been fabulous throughout this journey. I will be incessantly grateful.

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LIST OF PUBLICATION

In the process of finalizing this dissertation, the contents were extracted and compiled for publications, as indicated below.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABBREVIATIONS AND ACRONYMS

AMOS	:	Analysis of Moments Structures
BI	:	Business Intelligence
CAM	:	Capital Market Authority
CB-SEM	:	Convariance based SEM
CDSC	:	Central Deposit & Settlement Corporation
CI	:	Competitive Intelligence
CIO	:	Chief Information Officer
CMP	:	Customer Management Capability
CPM	:	Corporate Performance Management
DCs	:	Developing Countries
ICT	:	Information and Communication Technology
IT	:	Information Technology
IMC	:	Information Management Capability
IS	:	Information Systems
KTB	:	Knowledge Based Theory
OLT	:	Organization Learning Theory
OLAP	:	Online Analytical Processing
RBV	:	Resource Based View
ROE	:	Return on Earnings
ROI	:	Return on Investment
PLS	:	Partial Least Square
PMC	:	Process Management Capability
SEM	:	Structural Equation Modelling
VRIN	:	Valuable, Rare, Inimitable, Non-substitutable

ABSTRACT

While the Business intelligence (BI) initiative has been a top priority of Chief Information Officers around the world for several years and accounting for billions of dollars in capital expenditure, the academic research on the actual benefit derived from this investment remains sparse. Available literature on how insights triggered by BI are transformed into profitable business learning is vague and fragmented. Even when the benefits have been identified, it is difficult to measure because of their indirect and delayed effects on business performance. Hence, the main objective of this study was to determine the relationship between BI capability, organisational capability, complementary resources and performance of firms listed at the NSE. The study used interdisciplinary theories to achieve the research objective, namely; Information Systems Capability Theory, Organisational Learning Theory and Knowledge Management Theory. Furthermore, the study was performed using a mixed methods research methodology. Through a cross-sectional survey, the researcher collected data using a structured questionnaire for quantitative strand of the study. The study used structural equations modeling technique (Partial Least Squares approach- SEM-PLS) to analyse quantitative data and validate the developed research model. Thematic analysis aided by Atlas.ti version 8 software was applied to analyse qualitative data. Findings of quantitative and qualitative strands of the study were triangulated based on the convergent parallel design. The results indicated technical dimension related factors; quality of data sources, user access, interactive capability and vendor selection, human capital related factor; knowledge management, organisation dimension related factors, service level agreement and risk management have positive and significant effect on performance. However, the relationship is moderated by organisational capability related factors; customer management capability, process management capability and performance management capability. The relationship is also mediated by complementary resources that comprise BI champions, culture, decision making process and organisation strategy. Findings from this study also demonstrated that the combined effect BI capability, organisational capability and complementary resources on firm performance is significantly greater than that of the individual effect. The study contributed to theory by building a framework for BI assessment, including factors that significantly lead to improved performance. The results of this study also provide new insights into the existing business intelligence literature researchers can employ to aggrandize knowledge. The study proposed the use of longitudinal study capture to delayed BI benefits. The importance of management to exploit value from unstructured data is highlighted. Furthermore, the study suggests directions for future research with implications for academia to validate emerged factors using quantitative approach.

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

The prevailing global business environment is fast changing, complex and characterized by enormous amounts of data originating from social networks and mobile communications, in addition to traditional databases. Accessibility to reliable and adequate information in a timely manner is of paramount importance for a firm to develop a competitive edge, with eventual impact on performance in the prevailing business environment (Shollo, 2013). Unfortunately, the high volume of data generated cannot be handled by traditional technologies and programming paradigms (Sirin & Karacan, 2017; Baars & Kemper, 2008). However, rapid advancement in technologies in the last decade has made processing of data easier, subsequently enabling firms to handle huge volumes of data at excessive speed and in various forms such as images, web pages, emails and sales force reports (known as "big data") (Sirin & Karacan, 2017). The concept of Business Intelligence (BI) has gathered a broad recognition and it's deemed to be a cornerstone for the organization success in the advent of globalization (Sebanescu, 2012; Işık, Jones, & Sidorova, 2013). BI centres on remodeling raw data into usable, valuable and actionable facts (knowledge). New knowledge generated contributes to success of an organization by enabling stakeholders make better decisions and take appropriate actions (LaValle, Lesser, Shockley, Hopkins, & Kruschwitz, 2011).

Application of BI has a positive impact on firm performance (Brynjolfsson, Hitt & Kim, 2011; Anderson-Lehman, Watson, Wixom & Hoffer, 2004; Fink, Yogev & Even, 2017). Investment by Michigan State University in BI generated an annual savings of $34,434 and 55% return by eliminating manual data analyses thereby enabling staff to focus on value adding activities (Durcevic, 2018). A study of over 400 Information and Communication Technology (ICT) experts sampled from ninety-three countries indicated that BI is one of the key investments in firms (Arefin, Hoque, & Bao, 2015; Yiu,Yeung, & Cheng, 2021). Global BI investment stood at $18.3 billion in 2017. The market was values at $22.8 billion by the end of 2020 (Moore, 2017) and it is projected to reach $ 29.48 billion in 2022 (Sanyal, 2021). In Kenya, ICT spent has been growing at 11% per year, from $3.11 billion in 2016 to $4.26 billion in 2019 (Kenya National Bureau of Statistics, 2019). Elbashir, Collier and Davern (2008) posit that this magnitude of spending on BI is an indication of its strategic significance and brings forth the need for more scholarly research in this area. BI literature is fragmented on how BI impact performance (Audzeyeva & Hudson, 2016) and lacks a general framework to integrate findings on moderating and mediating variables (Trieu, 2017; Eybers, 2015).

Theoretical foundation underpinning this study includes Information Systems (IS) Capability Theory by Peppard & Ward (2004), Knowledge Based theory by Grant (1996) and Organisational Learning theory advanced by Fiol and Lyles (1985). IS capability theory advances the concept of BI capability. Knowledge Based Theory and Organisational Learning Theory included to appreciate how information from BI facilitate learning, thereby generating new knowledge that result in improved decision making. While BI capability influences development of organisational capabilities, these capabilities are in turn antecedents of superior firm performance (Kohli & Grover, 2008). However, complementary resources mediate the relation between BI and performance.

Emerging Fintech companies in Kenya have accelerated the volume of data generated by corporate entities. For example, volume of mobile transactions increased from $148 million in 2017 to $40 trillion in 2018 in the financial services sector, that account for 31% of all listed firms at the Nairobi Securities Exchange (NSE) (Fintech Impact on Kenya's Financial Services Industry, 2019). In recent years, several NSE companies have issued profit warnings, an indication of poor performance due to stiff competitive environment. For instance, Bamburi Cement, Deacons, HF Group, Sanlam, Kenya Power and Sameer Africa in 2018 (Kinuthia, 2018). Data is recognized as a resource and can be exploited by the use of BI systems to improve profitability and competitiveness (Williams, 2016), thereby revising downward trend of these listed firms. Furthermore, due to shorter product life cycle, change in social values and demographic patterns, these firms operate in a moderate to rapidly changing business environment (Audzeyeva & Hudson, 2016). Thus, the capability to detect and respond to such changes should be developed. In this respect, opportune intelligence on the organization, its operations, as well as its business associates, must be readily accessible to enlighten decisions and actions aimed at achieving or maintaining a competitive market advantage (AL-Shubiri, 2012). BI impact is realised through improved fact-based decision making, improvement in business processes, innovation and environmental adaptation (LaValle et al., 2011; Brynjolfsson et al., 2011; Audzeyeva & Hudson, 2016). Barua, Mani and Mukherjee (2012) posit that firm's profitability increases by 16% for a 10% improvement in data quality and sales mobility. Moreover, Watson and Wixom (2007) concluded that with correct capabilities, BI can help an organization forecast variations in product demand or spot an increase in the market share of a competitor's product and react rapidly by introducing a competing product. However, the extent to which BI, organizational capabilities and complementary resources impact performance has not received much attention (Jourdan, Rainer & Marshall, 2008). The aim of the study is to investigate what effect BI has on the performance of firms in the Kenyan context.

1.1.1 Business Intelligence Capability

The term BI was conceptualised in the 1800s, but it was only in the 1900s that its use was widespread, after BI was applied by Dresner, a Gartner analyst to advance the notion that data in IT system can be used by individual firms (Shollo, 2013). Several definitions of BI have been forwarded in both practice and academia (Işık, Jones & Sidorova, 2013). For example, AL-Shubiri (2012) defines BI as a system that incorporates operational data with analytical tools to present valued information to key stakeholders. Olszak (2014) and Jourdan et al. (2008) argue that BI is composed of both organizational and technical components. From a technical perspective, BI is a combined assortment of tools, technologies and software applications in use to gathering of data from multiple sources, data analysis and making it broadly accessible to stakeholders (Olszak, 2014). From an organizational view, BI stands for a holistic and advanced approach to support decision-making across the organization (Isik et al., 2013). Vendors of software and consultancy firms have defined the term to conform to their products and services. Hence, BI as a term is still growing in terms of definition and does not have a universally accepted definition. This study adopted the definition by Gartner group, which states: "BI is a broad term that comprises tools, applications, infrastructure and best practices that provide accessibility and analysis of data to optimize and improve decisions as well as business performance"

(Business Intelligence - BI, 2016). The definition was embraced because it encompasses both technical as well as organizational perspectives. According to Popovič, Hackney, Coelho & Jaklič (2012), BI systems have several features, distinct from other technologies. First, BI is primarily a managerial user tool. Hence, specific efforts are required to develop acceptance for its use. Second, the actual use of this tool is generally voluntary and therefore, users might want to see the advantages of using it. Third, organizations implement this application for strategic reasons with indirect and long-term benefits (Kulkarni, Robles-Flores & Popovič, 2017).

The BI capability concept emanates from IT capabilities (Kulkarni et al., 2017), which scholars have studied extensively in the information systems (IS) literature, for example, Bharadwaj (2000). According to Bharadwaj (2000), IT capability is an organizational capability to organize and deploy IT-based resources together with other available resources to yield competitive advantage. Thus, beyond technology, firms rely on other resources to build unique capabilities that are difficult to imitate (Gupta & George, 2016). Kulkarni et al. (2017) remarked that BI capability particularly deals with the dissemination of information and its analysis for making decisions by management to take decisions. Drawn from IS Capability theory, BI capability refers to critical functionalities that help organizations to continually derive and leverage value through BI (Peppard & Ward, 2014; Olszak, 2014; Isik et al., 2013). Fink et al. (2017) argued capabilities are the primary source of value and are often viewed as a catalyst for transforming organisational assets into a competitive advantage. In their contribution, Schlegel and Sood (2007) identified 12 BI capabilities, which they grouped into 3 categorizes namely information delivery, integration and analysis. Mithas et el. (2011) discussed intensively this concept of capability and brought forth a comprehensive definition as the ability to first, provide user information that is secure, confidential, time bound, accurate, and reliable; second to ease accessibility and connectivity that is within reach and has adequate range; and third to align infrastructure with emerging business requirements. BI capability triggers sustainable competitive advantage and consequently impacting performance (Arefin et al., 2015). Isik et al. (2013) took this concept a step further by looking at the role of BI capabilities from both an organizational and technical standpoint. In addition, the authors identified nine BI capabilities that were used in this study. Flexibility and risk management support were categorised under organisation perspective. Under a technical perspective, the authors classified data type quality, interaction, user accessibility, data source quality, and reliability. Human capital is also a critical resource, according to the literature (Bharadwaj, 2000; Stevens, 2010; Hatch & Dyer, 2004). Hence, human capital dimension was included under BI capability.

The data source can be specified as the location where the data used for assessment is stored and extracted (Isik et al., 2011). Negash (2004) espoused that BI can load data from both external and internal sources. Internal data is usually sourced from traditional BI application management facilities, such as data warehouse and covers areas like finance, operation and human resource. External data is produced during communication with customers, and vendors and is rarely stored in a data warehouse. It is often obtained from websites, worksheets, voice recordings, and video files. Isik et al. (2013) pointed out that BI system effectiveness and the extent to which the users are satisfied by the output, is impacted by the quality of the data source. Importance of data from external environment pertaining to political, economic, social and technological dimension has been highlighted (Shollo & Kautz, 2010).

Data type relates to the nature of the data; numeric (structured) or non-numeric (semi-structured) (Isık et al., 2013; Sirin & Karacan, 2017). Structured data is data that can be evaluated and analysed utilizing statistical methods such as averages and percentages, for example, financial data. Negash (2004) describes semi-structured data as the data, which does not dovetail into relational or flat files. For example, data in text, sound or images. The author maintains that there are no fully unstructured data hence, the term semi-structured data. In this study, structured data is referred to as quantitative data and semi-structured data as qualitative data. BI has traditionally depended heavily on quantitative data (Sirin & Karacan, 2017). However, myriad sources of information contain qualitative data, such as web pages with information about competitors, reports from the sales force and repositories of research papers (Baars & Kemper, 2008; Negash, 2004). Although studies suggest that data quality is a BI crucial success factor (Yeoh & Koronios, 2010), Isık et al. (2013) reported that the quality of qualitative data has been given less attention than the quality of quantitative data.

Interaction capability encompasses connecting different systems (for example, knowledge repositories, ERP, transaction systems and CRM) and their data or applications jointly, be it functionally or functionally, so that more value can be produced beyond what each system provides (Sabherwal & Becerra-Fernandez,2011). Interaction capability offers a unified perspective of the company processes to relevant stakeholders for decision-making (single version of truth). The level and quality of integration between BI and other systems is essential to guarantee accurate BI outcomes. However, it is a challenge to many organizations (Shollo & Kautz, 2010; Baars & Kemper, 2008). More specifically for firms that utilize data from diverse sources and transmit the same into other information systems. Effective communication between these systems has a direct impact on overall results. BI integration can take place at the data level, business process level, application level or customer level, though these levels are not independent of each other (Isık et al., 2013). Hence, the need for organisations to discover methods to effectively handle BI integration with other information systems (Shollo & Kautz, 2010).

User access. BI tools serve a specific purpose due to varying capabilities. One size BI does not suit all the requirements. Taking into consideration organisations have various user groups, it is imperative to use separate BI applications with distinct methods of access relevant to their requirement (Watson & Wixom, 2007; Isık et al., 2011). While a number of organisations implement BI systems that offer all users with unrestricted access to data analysis and reporting tools, others provide comparatively limited access (Havenstein, 2006). Although most web-based applications are comparatively simple to use, desktop applications are primarily devoted to particular users and provide customized functionality for effective evaluation. Building and managing multiple user access methods and supporting a variety of analyses is a critical BI capability (Isık et al., 2013). The authors argue that access demands of users in an organization differ. At the operational level, for instance, users may need to monitor essential processes and have access to current time information, while senior executives may need to track the execution of strategic goals throughout the organization and thus warrant distinct levels of access from operational users. It is crucial that organizations review access levels (Olszak, 2014) to enable BI users access data in reference to kind of decisions they make.

Reliability of data relates to accuracy and dependability of data to be processed for decision-making (Isik, Jones& Sidorova, 2011). While BI system makes data analysis easier, the quality of data to be analyzed is paramount. Empirical evidence suggests that organizations are adversely impacted by unreliable data. For instance, the Gartner Group estimates that over 50% of BI projects failed in 2007 due to issues relating to data reliability (Graham, 2008). Isik et al. (2011) pointed out reliability of data can be an issue when collected from external sources, for example, data from internet blogs. Poor data processing, bad data maintenance methods and migration process mistakes from one scheme to another can as well impair reliability of internal data.

Flexibility. The capability of BI to provide decision support when variations exist in the business processes, technology or the business environment in general is termed as flexibility (Gebauer & Schober, 2006). One of the most important factors to consider is flexibility when choosing the underlying technology to support BI operations in order to gain competitive benefits offered by BI solution (Isik et al., 2013). The system should ideally be consistent with current applications to reduce further customisation cost. Isik et al. (2013) further posit that stringency of the BI-supported business process rules and regulations directly affect BI's flexibility. If the application includes rigid sets of policies and rules, BI will have comparatively low flexibility. According to Isik et al. (2011), technology doesn't always accommodate all exceptional situations hence, organisations need flexibility to maximize BI's potential. While inadequate flexibility can deter the system from being used in certain situations, excessive flexibility can boost complexity and decrease usability (Gebauer & Schober, 2006).

Skills and BI experience. According to Tayles, Pike and Sofian (2007), human capital refers to skills, knowledge, experience and innovativeness of staff in the organisation. Bharadwaj (2000) classified human capital as IT resources. The author identified two crucial dimensions of human IT resources; technical IT skills and managerial IT skills, for example, interaction with other stakeholders. These skills typically develop over a lengthy period through the accumulation of experience. Stevens (2010) asset human capital is acknowledged as the tactical value of human assets in the organisation that originate from the entire workforce. The author further clarified that human capital is not the head count in the business, but it is what that individual brings and adds to the achievement of the organisation. As staff in organisations advance with age, they obtain a set of knowledge that is tailored to the company's activities, culture and structure (Tayles et al., (2007), hence the need to harness and manage this knowledge. Similarly, Fraiha (2011) observed that diversity and knowledge of staff are factors that influence business values from IT. Diversity may be seen in terms of age, education, gender, nationality and other characteristics. This brings forth the need to share BI experiences. According to Hatch and Dyer (2004), human capital is presumed to be rare, inimitable and irreplaceable owing to its social complexity, making it a distinctive resource.

Risk Management. There are risks in all facets of our lives and hence, in recent decades, risk management has become a key topic in both academia and practice (Wu, Chen & Olson., 2014). In every business, risk and degree of uncertainty exist. Hence, some organizations use BI to reduce variations and uncertainties and make better informed decisions. Isik et al. (2013) termed this approach to risk management as an organisational capability. The BI's capabilities affect how the company manages risk successfully. BI can assist an organisation handle its risks by tracking the organisation's financial and operational fitness and regulating its activities via Key Performance Indicators (KPIs), warnings and dashboards (Isik et al. (2013). According to You et al. (2021) BI systems improve the sales forecast, resulting in a better business planning, for instance, deciding on the optimal level of production and timing while reducing unwanted setups. Wu et al. (2014) observed that BI models are indeed helpful in dealing with market risks, default risk, and operational threats. For instance, Wu and Olson (2010) showed how predictive scorecards had been used to evaluate credit worthiness of customers in a bank.

1.1.2 Organisational Capability

Mithas et al. (2011) established the organisational capabilities that connect firm performance and BI capability. These capabilities include process management, customer management and performance management capability. Customer management capability (CMC) is the ability to generate and sustain customer relationships. The authors observed that this capability allows an organisation to utilize customer’s voice to obtain market information and single out business opportunities. BI capability is a key factor in enabling firm's CMC (Mithas et al., 2011). Effective BI capabilities facilitate capturing of customer information and propagate to relevant stakeholders. Shared information between customer service units and IT units affects the capacity of the firm to obtain more customer intelligence (Ray, Muhanna & Barney, 2005).

Performance management refers to the capacity to create requisite monitoring and check systems to examine the performance of business. It permits firms to align strategic and operational goals with business operations in order to fully sustain performance via better and informed decision-making and action (Bogdana, Felicia & Delia, 2009). It encompasses the choice of suitable measurement methods, data collection and data analysis. An effective performance management system can enable a firm to detect unfavourable variations, ascertain sources of variation and implement new strategies in an attempt to find a viable solution (Mithas et al., 2011).

Process management capability is the capacity to create a procedure with effective scope and wealth for steering the firm's activities. Rayat and Kelidbari (2017) define a process as a series of mutually dependent actions, which translates inputs to outputs in a stepwise manner by utilising one or a number of inputs. An individual organisation undertakes a number of sets of actions in order to realize its strategic objectives hence, creating numerous avenues for the application of IT to streamline business operations (Melville et al., 2004). BI capability permits a quicker and more responsive redesign and configuration of processes in reaction to shifts in business environment, which in turn enhances organisational performance.

1.1.3 Complementary Resources

Complementary resources are assets (Teece, 1986) that help in generation of technology related benefits (Christimann, 2000). Competitive advantage is gained when a firm integrate and deploy available resources (Gupta & George, 2016; Bharadwaj, 2000). According to Barney (1991), these resources are firm controlled and include wider organisational capabilities that help to realize values from IT investment. Complementary resources were further categorized by Melville et al. (2004) to includes culture, organisation strategy, and structure and decision making process.

Deshpande and Webster (1989) defined culture as the patterns of common beliefs and values that help people understand the operation of the organization and thereby providing behavioural standards within work environment. Culture promotes a healthy and favourable atmosphere and consequently contributing to the flow of information between various stakeholders. Denison, Haaland and Goelzer (2003) posit that culture has four dimensions; adaptability, involvement in work, consistency and mission. Adaptability refers to the degree to which an organisation can respond to the external business environment by changing its behaviour, systems and structure. Consistency relates, according to the authors, the extent to which the organisation has the drive to maintain shared values, beliefs and standards among its workforce. Mission relates to the organisation's clear and meaningful goals that all staff share. Dension et al. (2003) argued that a powerful and supportive culture enhances the capacity of employees to digest data from different sources for efficient decision-making. Arefin et al. (2015) concluded that BI systems determine an organization's effectiveness and depends on corporate culture.

Organizational strategy is a plan of achieving organisational goals through interaction with environment. BI systems cannot work in isolation but within the context of competitive environment and organisational factors such as strategy to enhance performance (Arefin et al., 2015). The study enlisted four dimensions that were validated by Bergeron, Raymond and Rivard (2004) and include analysis, defensiveness, futurity and pro-activeness. Defensiveness is exemplified by cost reduction and efficiency, while pro-activity is articulated through taking a step forward to exploit opportunities such as diversification and acquisition of businesses (Arefin et al., 2015). Analysis is evidenced by thorough research to identify the root causes of the problem. Futurist is articulated through decisions that take cost effectiveness into account at the outset and also in future.

Organization structure refers to forms of authority, communication channels and nature of relationships that exist in an organisation. Rayat and Kelidbari(2017) assert that structure entails duty allocation, reporting formats and interaction patterns that emanates therein. According to Arefin et al. (2015), common variables associated with structure are centralization and decentralization. The authors argues that BI systems seem efficient and affect the performance of companies in a decentralized structure by providing information oriented to the processes, the customers and the suppliers immediately to the top authority. The process of making choices comprises singling out the problem, identifying various alternative solutions to the problem, analyzing identified alternatives and selecting the best alternative. Shollo (2013) observed that BI output is utilised by decision makers to tackle illogicality in the organisation and also to enhance legitimacy of their argument. Sharma, Mithas and Kankanhalli (2014) further argue that decision makers are in some cases limited by institutionalization of norms thus affecting the quality of decision and acceptance of the decisions thereof. Wixom and Watson (2010) assets that the use of BI enhances not only decision making but the quality of such decisions.

1.1.4 Firm Performance

Performance is a multidimensional construct. It concentrates on the application of economic performance pointers such as revenue increase, profitability, and market share (Melville et al., 2004). It also includes non-financial indicators such as product quality and customer satisfaction (Trieu, 2017). Efficiency and effectiveness of an organization is related to performance (Elbashir et al., 2008). Previous studies have either taken an objective or subjective approach to measuring firm performance (Aydiner et al., 2019). The subjective approach is based on the perception of the executive due to inherent limitations in using objective or quantitative performance measures. For example, Aydiner et al. (2019) argue that many firms do not disclose adequate financial data and any available objective measures in financial statements are flawed hence, not suitable for research.

In an effort to measure performance, Kaplan and Norton (1996) proposed Balanced Score Card (BSC) framework composed of four perspectives namely customer, internal process, organization learning and growth and financial. This approach assesses financial as well as non-financial performance. Researchers in IS have operationalized company-level performance through operational measures (such as cost reduction, profitability, customer experience, time to market and return on investment) and market-based measures (such as change in stocks valuation, revenue growth and innovation) (Gu & Jung, 2013; Richard et al., 2014; Ida & Graeme, 2015). However, this study adopted Malcom Baldrige National Quality Award (MBNQA) framework that explicitly gauges IT-enabled information flows (Ghosh, Handfield, Kannan& Tan, 2003). In addition, the dimensions used satisfy Wade and Hulland (2004) criteria for suitable dependent variables to evaluate IT enabled benefits that should reflect trends and competitiveness. The Malcom framework has been used by other researchers such as by Mithas et al. (2011) to validate the four dimensions of performance adopted in this study. The dimensions include human resource, customer-focus, financial, and organisational effectiveness, to assess BI impact on performance of listed firms at NSE.

1.1.5 Firms listed at the Nairobi Securities Exchange

Based in Kenya, the Nairobi Securities Exchange (NSE) is a leading East African stock exchange and ranks fifth largest in Africa (Nairobi Security Exchange, 2018). It was established in 1954 and its functions are regulated by Capital Markets Authority's authority of Kenya. It provides a world-class platform for issuing and trading debt and equity securities. In 2011, the Nairobi Stock exchange changed its name to Nairobi Securities Exchange. The re-branding was a component of a strategic move to include a comprehensive range of exchange securities services. The NSE currently offers a platform for investing, clearing and payment of equity, debts and other related instruments.

This study focused on NSE listed companies representing Kenyan economy’s major sectors. There were sixty-four listed companies representing different sectors namely, agricultural, automobile, banking, commercial and services, construction energy, insurance and investment by the end of 2018 (Nairobi Securities Exchange, 2018). Improvement in stock indexes maintained by NSE (such as 20-share Index) is a yardstick for economic performance. The NSE plays a leading role in spurring economic growth by facilitating exchange of funds to gainful undertakings, and subsequently aiding the discerning and proficient allotment of capital (Nairobi Securities Exchange, 2018). However, recent year’s performance of some of the listed firms has been on the spot. The NSE 20-share index declined from 3607 points to 3285 points in 2018, a 9% drop (CMA Annual Reports, 2018). Several firms issued profit warnings in 2018, largely attributed to the generally tough economic environment (Kinuthia, 2018).

Listed firms at NSE can exploit opportunities presented by BI applications to track shifts and patterns in the business environment (both internal and external) for the purpose of formulating best strategies aimed at maximizing shareholders return. The choice of listed companies for the study is justified by the availability of objective and reliable economic/financial performance data, having invested in this technology.

1.2 Research Problem

The concept of organizational performance holds a central position in business management as well as in the field of organizational research. IS capability theory affirms that to remain competitive in such environment, a firm must harness available resources to generate value. One of these critical resources is BI. Elbashir et al. (2008) observed that the ongoing magnitude of investment in BI is an indication of its strategic significance. Continental Airlines invested £30 million in BI and achieved a 1000% return on investment (Anderson-Lehman et al., 2004). Investment by Michigan State University in BI generated a return of 55% (Durcevic, 2018). Processing of huge volume unstructured by data by Walmart led to an increase of 10-15% in online sales annually (Liu, Han, & DeBello, 2018). Nevertheless, how BI provides benefits is yet to be addressed in literature (Ida & Graeme, 2015; Kulkarni et al., 2017). Besides, other studies such as Chae, Koh and Prybutok (2014), have underscored the negative impact of IT on performance. Similarly, Carr's (2003) study highlighted the non-significant effect of IT investment. A survey conducted by Henshen (2008) on BI impact, reported a 19% success rate on business performance. Kmart sales decreased from $37billion to $12.1 billion, notwithstanding the investments in this solution (Liu et at., 2018). Despite the concerns raised on IT investment in the aforementioned studies, significant investment continues to be made in BI systems (Yiu et al., 2021) with the investments in these systems approximating $18 billion in 2017 from $17 billion in 2016, and with a projected growth to $22.8 in 2020 (Moore, 2017).

In Kenya, ICT expenditure increased from $3.11 billion in 2016 to $4.26 billion in 2019 (Kenya National Bureau of Statistics, 2019). However, in contrast, the performance of corporate institutions, especially those listed at NSE, has been declining (Kinuthia, 2018). Recent profit warnings by listed firms have led to a significant decline in share prices, consequently eroding investor's value. NSE plays a critical role in the economic growth hence, good performance in these companies is imperative. Stringent reporting requirements by Capital Markets Authority (CMA) with a view of promoting market integrity has compelled listed firms to increasingly consume vast amounts of data hence, the drive to invest in BI systems. Given substantial amount of money spent and lean scholarly research in this area (Trieu, 2017), the need for more studies on the impact of this technology is imperative (Elbashir et al., 2008).

Empirical studies conducted by various researchers on the role of organisational capabilities revealed various shortcomings (Melville et al., 2004; Richards, Yeoh, Chong& Popovic, 2014; Chen, 2012). Mithas et al. (2011) carried out a study on how information capability influences performance. The study confirmed BI impact in developing organisational capabilities and this by extension, influences performance through customer, management and process capabilities. This implies that the link between BI and performance is moderated by organisational capability. Further research by Yogev et al. (2013) on value creation by BI, shows that by enhancing operational and strategic business processes, value is generated. Xu & Kim (2014) reported that performance is influenced through the enablement of dynamic capabilities, which facilitates sense and reaction strategies to environmental shifts. Eybers (2015) noted a positive impact on performance but did not explicitly elucidate the variables that moderate noted impact. Aydiner et al. (2019 has recently echoed the need to take further steps to open the black box linking IS capabilities and performance by using appropriate mediating/moderating variables.

Most of the existing expositions are insignificant because they lack the inclusion of identified complementary resources (Richard et al., 2014; Melville et al., 2004) and thus, Elbashir et al. (2008) accentuated the need for more research focusing on mediators. Mithas et al. (2011) observed the relationship between BI and performance is influenced by strategic planning and leadership. Yogev et al. (2013) noted that exploration and exploitation activities in the organization has an effect on BI-Performance relationship and suggested other factors such as culture should be included in future research. Contributing to the foregoing argument, Arefin et al. (2015) states that the effect of complementary factors such as process, culture, structure and strategy on BI systems has remained largely unexplored. Trieu (2017) summarised this ongoing debate by stating that BI literature is fragmented and lacks a general framework to incorporate the findings and systematically guide research. Talaoui and Kohtamäki (2020) attributes ascertained fragmentation to duplication of identical efforts in BI research. Božič and Dimovski (2019) concluded that the process of transforming the insights triggered by BI into profitable business learning remains vague, henceforth calls for more studies to investigate this complex phenomenon.

Extant literature on BI studies also indicates that substantial empirical studies have been conducted in developed countries. For example, the effect of BI on operational process of firms (Elbashir et al., 2008) in Australia, critical success factors for BI (Yeoh & Koronios, 2010) in Australia, BI best practices (Wixom & Watson, 2010) in the United States, BI impact on organization effectiveness (Arefin et al., 2015) in China and BI maturity models (Dinter, 2012) in German. Regionally, the few studies conducted on BI have been skewed towards maturity models. For example, Buchana & Naicker (2014) on the impact of Mobile BI on decision making in South Africa and Owusu, Agbemabiasie, Abdurrahaman and Soladoye (2017) on BI adoption in Ghanaian banks. However, IT advancement differs across developed and developing countries (DCs) and with technology advancement in DCs lagging behind developed nations. What is also unique with DCs, according to Avgerou (2008), is the fact that the pace and direction in IS innovation is set by industrialized countries (different environment). This study aims to bridge this gap by conducting research on listed firms at NSE, a context of a developing country.

Studies carried out on BI impact have adopted either qualitative or quantitative empirical methodologies, with mixed methods studies lacking (Venkatesh, Brown& Bala, 2013; Mingers, 2001). Findings from peer reviewed studies on BI conducted by Ain et al. (2019) between 2000 and 2019 revealed that 56% of published papers embraced quantitative approach, 19% were based on qualitative approach, while 11% adopted mixed methods approach. Mixed method mitigates the weakness of qualitative and quantitative approaches (Johnson, Onwuegbuzie & Turner, 2007; Yu & Khazanchi, 2017). While quantitative research is simple and capable of generating superficially robust findings that can be generalized from samples to populations, it does not sufficiently explain social realities. Qualitative research is subjective and provides limited generalization. However, it has the ability to capture the fundamental meanings of a social phenomenon and thus more accurately explains social realities (Haq, 2014). Mingers (2001) has underscored the importance of applying multiple paradigms in IS research to gain a complete understanding of a social phenomenon. It provides reliable and richer findings (Johnson et al., 2007; Mingers, 2003). Yu and Khazanchi (2017) exemplified that mixed methods approaches are gainful in studying intricacies and interactions implicitly in IS phenomenon, especially when area of investigation is fairly new. According to Talaoui and Kohtamäki (2020), there is scant knowledge of interrelationships between the BI process and the organizational context. Hence, a mixed method was adopted for the purpose of obtaining a fuller picture and a deeper understanding of BI impact (Venkatesh et al., 2013). This study seeks to answer the following question: what is the impact of BI on firm performance taking into consideration the role of organizational capability and complementary resources?

1.3 Research Objectives

The objective of the study is to establish the relationship between BI capability, organizational capabilities, complementary resources and performance of firms listed at the NSE. The specific objectives of the study are to:

a) Establish the influence of BI capability on firm performance.
b) Establish the influence of complementary resources on the relationship between BI capability and firm performance.
c) Establish the influence of organisational capabilities on the relationship between BI capability and firm performance.
d) Examine the effect of BI capability, organisational capability and complementary resources on firm performance.

1.4 Value of the Study

This study helps build the emergent literature on the benefits of investment in BI systems in developing countries. There has been a growing concern by researchers and practitioners on the business worth of the huge resources invested by firms in IT and continues to elicit widespread debate (Richards et al., 2014; Melville et al., 2004). The study offers empirical evidence that BI capability, complementary resources and organizational capability are critical in enhancing firm performance. Hence, the study accentuates the need for investment in BI solutions to enhance performance.

Second, the study also gives light through consolidation of IS capability theory, Knowledge based theory and Organization learning theory into a single theoretical framework. The theoretical perspective adopted and the research framework applied will provide additional useful material to those wishing to pursue academic research in this area. Therefore, the study advances knowledge on BI impact by developing an integrated framework that provides a multi-perspective understanding of BI capability for companies listed on NSE.

In reference to methodology, the study was guided by Mixed methods approach that involves combining elements of qualitative and quantitative strands. The study has complemented empirical investigations that have employed Mixed methods in IS. The benefit of this approach includes the ability to harness the strength of different methods, provides deeper insights into phenomena that are enigmatic when only using quantitative or qualitative methods, tackle research issues involving real-life understanding of the context, multi-level view and influence of culture. To analyse quantitative data, the Partial Least Square SEM (PLS- SEM) was employed. This is a second-generation analysis tool that can undertake extensive evaluation of different variables and their connections in a single comprehensive check. It also offers the researcher an opportunity to model the dealings among manifest and latent constructs. Specifically, SmartPLS version 3.0 was employed to analyse the data. A detailed guideline on how to run required reports and tests in using this software has been encapsulated

Finally, the study highlights useful insights for managerial practice by examining the impact of BI. It fills prevailing knowledge gap by providing a better understanding of this innovation. Such information will be beneficial to management in understanding the importance of adopting BI to secure opportunities of success in decision making process, thereby enhancing competitive advantage and productivity. The current study has presented optimal BI capabilities, complementary resources, and organisational capability that enhance performance. The teams in the organisation charged with selecting, developing and exploiting BI solutions with be guided by the findings of this study.

1.5 Organization of the Thesis

The study is arranged into seven chapters.

Chapter one gives a base of introduction to the study. It highlights a concise outline the thesis concept that include BI capabilities, Organisational capabilities, complimentary resources and performance. This section also describes the context of the study, the research problem, objectives and the value of the study.

Chapter two of this thesis is soaked to the review of literature. The chapter begins with the discussion on theories underpinning the research preceded by a literature review of construct identified. The section also includes a summary of previous studies as well as the gaps that this study aims to fill. It also presents initial conceptual framework and research hypotheses.

Chapter Three presents a detailed research methodology. Several research paradigms are discussed with a view to selecting appropriate study research methodology. The chapter also describes the research design, study population and data gathering procedures. This chapter similarly displays operationalization and measurement of variables employed in the study. The results of the data's reliability, normality and validity tests are also presented. The procedures for data analysis for both quantitative and qualitative aspects of the study are discussed.

Chapter four present detailed data analysis and interpretation of the findings from quantitative data. It covers data preparations and descriptive statistics of the variables. Other areas covered include assessment of measurement model, structural model assessment, discussion on the findings and finally, implication.

Chapter five presents qualitative data analysis. The chapter covers demographic information and thematic analysis process using Atlas.ti software. Discussion and thematic analytical findings are also presented.

Chapter six discusses the results from the quantitative and qualitative threads of the study. Also presented is a new model focused on triangulated final results.

Chapter seven provides the thesis summary, conclusion and recommendations, research limitations and suggestions for further studies.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter brings on board theoretical, conceptual and empirical literature review. It presents a review of earlier studies on all the variables to highlight the gaps in knowledge. The chapter presents a summary of knowledge gaps which the study seeks to address through empirical research using the proposed conceptual framework. The hypothesis guiding the study is also included in this chapter.

2.2 The concept of Business Intelligence

The concept of business intelligence is not new from a historical perspective.The term BI was designed in the 1800s but its use only widespread in the 1900s after Dresner applied BI to advance the idea that data can be used in IT systems by individual companies (Shollo, 2013). BI is a natural outcome of a series of previous decision-making systems (Ida & Graeme, 2015; Yogev, Even, & Fink, 2013; Nagesh, 2004). Hence, several definitions of BI have been forwarded in both practice and academia (Işık, Jones & Sidorova, 2013). A study by Chen (2012) indicated that BI is a broad word that is composed of a set of technologies. Kumari (2013) defined BI as an ability of a firm to consolidate all its processes and capabilities and then transform them into knowledge to inevitably provide stakeholders with precise information at the appropriate time via the right channel. Zeng et al. (2006) regarded BI as a set of strong tools and approaches for the improvement of corporate decision-making, business activities and accelerating firms' value.

Olszak (2014) and Jourdan et al. (2008) assert that BI is composed of both organizational and technical components. From technical perspective, BI is a combined assortment of tools, technologies and software applications in use to gathering of data from multiple sources, data analysis and making it broadly accessible to stakeholders (Olszak & Ziemba, 2006). Chen, Chiang and Storey (2012) posit that BI technical perspective evolved in three phases: 1.0, 2.0 and 3.0. In the first phase of evolution, applications focus on processes for extraction, transformation and loading (ETL) for identifying appropriate data from transaction processing systems and placing them in the right analysis format.

Analytical technology adopted in this phase mainly consisted of statistical methodologies (Eggert & Alberts, 2020). Hence, technologies were developed to largely handle structured data collected by companies via various legacy systems (Chen et al., 2012). Prominent technologies that evolved under BI.1.0 phase include data warehousing, OLAP and data mining (Olszak, 2014).

BI 2.0, according to Olszak (2014) is typified by newer technologies, including opinion mining, web mining, semantic refinement, and mobile mining techniques. They focus on semi-structured or unstructured data processing, originating mainly from social media and the internet. Chen et al. (2012) ascertains that through various text and web mining techniques, huge amounts of data concerning customers or products can therefore be collected from the internet for strategic decision making. Web analytics tools like Google Analytics, for example, can provide a trail of user activities via customer click stream data logs, highlighting users' browsing and shopping patterns. BI 3.0 is characterised by collection and analysis data from different mobile devices and sensor data (Olszak, 2014; Eggert & Alberts, 2020). BI 3.0 are concerned with the analysis of huge quantities of sensor data. Mobile devices, for instance, smart phones and their entire downloadable ecosystems, are reshaping different social facets, such as the education and healthcare sectors (Chen et al., 2012).

From an organizational view, extant literature describes BI as a holistic and advanced approach to support decision-making across the organization (Isik et al., 2013; Olszak, 2014; AL-Shubiri, 2012). At the strategic level, BI helps to precisely set, monitor and achieve goals. BI enables various comparative reports to be carried out, for instance on historic results, valuation of particular offers, efficacy of distribution channels or the projections of future results based on certain assertions (Olszak, 2014). At the tactical level, BI may offer some basis for decisions in functional areas such as marketing, sales and finance. BI systems, in turn, are used at the operational level to perform ad-hoc assessments and answer questions concerning the continuous operations of departments and their current financial positions. Vendors of software and consultancy firms have defined the term to conform to their products and services. Hence, BI as a term is still growing in terms of definition and does not have a universally accepted definition. This study adopted the definition by Gartner group, which states: "BI is a broad term that comprises tools, applications, infrastructure and best practices that provide accessibility and analysis of data to optimize and improve decisions as well as business performance" (Business Intelligence - BI, 2016). The definition was embraced because it encompasses both technical as well as organizational perspectives.

2.3 Theoretical Perspectives

The study views BI impact through three lenses that is Information Systems (IS) capability, Knowledge Based Theory (KBT) and the Organisational Learning Theory (OLT). IS capability theory provides a mechanism though which an organisation can continually obtain value through adoption of technology (Peppard & Ward, 2004). This enables an organization to convert data into knowledge that has business value; consequently, it enhances its long run ability to adjust to changes (Weishäupl et al., 2015). OLT Theory leverages on the progress of learning arising from the firm's past mistakes over a period of time. KBT depicts organisations as the source of knowledge and competences that positively impact firms through services and products (Kogut & Zander, 1996).

2.3.1 Information Systems Capability Theory

IS Capability theory is rooted in Resource Based View (RBV) perspective (Peppard & Ward, 2004). The resource-based theory presumes that the resources required to design, select, and implement plans are heterogeneously allocated across firms and that such firm's uniqueness does not fluctuate over time (Barney 1991). According to Barney (1991), firm resources are those resources controlled by the entity geared towards improvement of efficiency and effectiveness. RBV holds that sustainable competitive advantage can only be realised when resources are valuable, rare, inimitable and non-substitutable (VRIN). RBV emphasises on the ability and capacity of the organisation to combine, integrate, review and reconfigure resources as the need arises (Barney 1991). The extent to which an organisation enjoys control over scarce resources determines issues pertaining to acquisition of skills, knowledge management, learning and know how as essential contributors to competitive advantages. Researchers have proposed multiple IT/IS resources that can generate competitive advantage. These resources include IT infrastructure, IT strategy/administration, and IT human capital (Yogev et al., 2013; Wade & Hulland, 2004). The extant literature on the RBV view indicates that investing in IT unaccompanied by other capabilities cannot assure desired benefits, because technology resources may not be VRIN (Peppard & Ward, 2004; Yogev et al., 2013; Olszak 2014; Chae et al., 2014; Aydiner et al., 2019). Competitive advantage is gained when a firm integrates and deploys available resources (Gupta& George, 2016). RBV theory has been criticized by Melville et al. (2004). The theory assumes resources are always used for their best purposes without clearly explaining how that is achieved.

Information Systems (IS) capability relates to firm’s ability to derive business value through deployment of competencies. Aydiner et al. (2019, p.170) defined capabilities as "*repeatable patterns of actions for the utilization of assets to create, produce, and/or offer products to the necessary environment*". Bharadwaj (2000) defined capibility as the capacity to assemble, integrate and use valued resources of an organisation. Hence, IS capabilities are core measures of a firm's ability to effectively implement and use IT systems (Aydiner et al., 2019). According to Peppard and Ward (2004), IS capability has three characteristics: flexible and IT infrastructure, fusion of business and IS knowledge and efficient use of business processes to link IS/IT assets with value realization. Peppard & Ward (2004) pointed out that underpinning IS capabilities is the IS competences, which are created when processes and structures are combined with IS resources (skill, knowledge and behavioural attributes). IS competencies determine the degree to which IT prospects are included in the business strategy, operations efficiency using systems and digital support, how efficient the IT infrastructure is developed, performance levels attained by IT operations and finally the capability of a firm to convey value from IT investment and exploitation. Aydiner et al. (2019) concurs that combination of resources and competences generates IS capabilities to eventually attain superior performance. Hence, a short fall in IS competence affects performance.

However, this theory has been criticized by Khani, Nor and Bahrami (2011) to the extent that it does not specify the nature of qualification, skills and capabilities, knowledge and capacity required for a firm to implement a successful information systems strategic plan. Isik et al. (2013) enhance this concept by looking at the role of business intelligence capabilities from both an organizational and technical standpoint. Isık et al. (2013) further identified nine capabilities of BI adopted in the research framework that encompasses: flexibility, management of risk, quality of data type, integration, accessibility of users, reliability and quality of data sources. According to Olszak (2014), BI capabilities can be integrated with available organisation resources, to acquire additional VRIN resources. The study settled on IS capability theory as the main anchor theory because of its tenets that guided the study in examining whether and how BI capability affects an organisational performance (Melville et al., 2004). In addition, as underscored by Cragg, Caldeira and Ward (2011), the framework is fair recent. Second, it comprehensively identifies competences that can be utilised by firms. Third, it focuses on the entire organisation. Finally, the framework provides an output from integrated methods of research, including previous literature and case studies encompassing action research and focus groups with managers from a variety of organisations.

2.3.2 Knowledge Based Theory

Knowledge Based Theory (KBT) postulates that knowledge is the most strategic and important asset of the organization (Kogut & Zander, 1992). According to Grant (1996), the theory asserts that human productivity has its source in knowledge. Knowledge is perceived to consist of skills, concepts and information corresponding to procedures and declarative difference made in cognitive sciences. The core premise of the theory depicted here is that knowledge which is largely tacit can be used to gain competitive advantage. Barney (1991) observed that it is difficult for competitors to imitate knowledge. The KBT views organisation as a repository of knowledge and competences where information is converted into value consisting of services and products (Kogut & Zander, 1996). Individuals develop and maintain knowledge. It can, however, become ingrained in the company as part of the organizational routines that are repeated on a regular basis (Grant, 1996). Kogut and Zander (1992) concluded that the key competitive dimension of a company is to effectively generate and transfer this knowledge within the organization. BI focuses on remodeling raw data from internal and external sources into information (knowledge) that is valuable in managing customers, processes and overall business performance.

The primary disparagement of this theory, according to Ahmad et al. (2013) is that KBT only considers employee power as a source of knowledge. Ahmad et al. (2013) opines that this is subject to the capacity of an individual to absorb. Furthermore, the capacity to absorb is motivated by identifying and applying enough knowledge in a friendly work environment. Ambiguity in the definition of knowledge, the primary construct of this theory, has been pointed out (Kaplan, Schenkel, von Krogh & Weber, 2001). The level of assessment at which knowledge is considered as a valid concept is not clear. This study holds that IT skills, knowledge and experience are IS resources (Peppard & Ward, 2004; Chae, Koh & Prybutok, 2014). When applied in organization processes to accomplish a given task, the outcome is the IS competence that underpins BI capability. BI capability contributes to organisational performance through learnt and shared knowledge.

2.3.3 Organisational Learning Theory

OLT asserts that for a firm to survive in a live environment, there is a need for a review of actions and processes that leads to the attainment of the set objectives (Larsen & Eargle, 2015). Notable contributors to this theory are Chris Argrys and Donald Schon (Weishäupl et al, 2015) and Fiol and Lyles (1985). Larsen & Eargle (2015) argued that for learning to occur, deliberate decision to adjust tact in responding to changing circumstances, connect action to outcome and the outcome has to be quantified. The authors observed that learning has three sections: data acquisition, interpretation and adaptation or action. Data acquisition (enabled by BI as applied in this study) is regarded as the beginning of the learning process. The second part is the interpretation by comparing actual to expected results. The third and final stage is adaptation and action. This stage occurs when the organization utilises the acquired knowledge to choose a new plan of action that is viable. The process of learning begins with individuals and when knowledge is ingrained within the organization, then it can be stated that organizational learning has occurred (Argote, 2011). Gupta and George (2016) stressed that businesses with high inclination towards learning, have stocks of knowledge that can be used to build huge data capability. Organizational learning is a valuable theoretical lens for understanding the impact of BI (Fink et al., 2017). The figure below summarises how learning is created in BI environment.

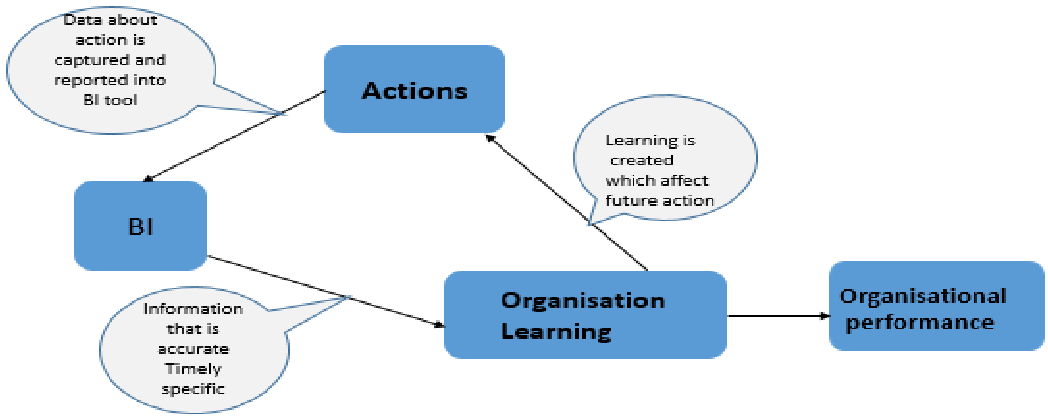

Figure 2.1 Learning and BI environment

Source: Adopted from Bara (2013)

However, Yadav and Agarwal (2016) critiqued this theory by observing that it is impossible to transform a bureaucratic organisation by learning alone. Several roadblocks such as organisation size and culture that do not support knowledge sharing hinder learning. Schilling and Kluge (2009) discussed intensively factors that either prevented or hindered the organization's learning. For example, organisation blame culture and elevated stress level often obstructs learning at the stage of intuition. Fear of ownership loss and control impedes learning at interpretation level. Moreover, according to Boi and Dimovski (2019), learning is influenced by individual absorption capacity, which is the ability to value new external information, internalize it, and utilize it to business decisions. This theory is critical in this study. It provides a foundation for the argument that, through learning, knowledge is generated within firms. Consequently, firm's ability to transmute knowledge to action, is central to organisational capability. This leads to better performance, particularly for listed companies in Kenya.

2.4 Business Intelligence and Performance

Adapting to current dynamic operating environment necessitates swiftness from firms and BI plays a pivotal function in improving this through the competences it provides. Previous empirical studies have confirmed BI has an impact on firm performance. Fink et al. (2017) study conducted in Israel confirmed the direct impact between BI capabilities and business value (at operational and strategic levels). The authors broadly classified the capabilities into BI infrastructure and BI team. The items selected under BI infrastructure adequately covered five indicators under technical dimension in this study and comprise reliability, flexibility, interaction, quality of data source and user access. BI team encompassed skills and knowledge. At the operational level, the impact is reflected in improved business process efficiency, as well as cost savings and product enhancement. Strategic value represents the ability to achieve organisational goals, besides improvement in financial performance. This was quantitative study. Data was taken from 159 respondents, via a cross section survey. The study, however, did not address the impact on other performance dimensions such as customer and human resources. Furthermore, the study relied on subjective BI utilization and organisational performance measures. Finally, the heterogeneous population surveyed in this study conveyed the unfounded idea that BI processes for creating value do not differ across industries.

Williams (2016) observed that the major quantifiable influence of BI adoption is value added, which is measured by return on investment. Qualitative study by Mithas et al. (2011) proved information capability has a direct impact on financial performance. Mithas et al. (2011) conceptualised capability as the potential to supply users with precise information, deliver accessibility and integration and the capacity to accommodate emerging needs. AL-Shubiri (2012) conducted research on 50 listed firms on Amman stock exchange, with findings indicating that BI has a positive impact in three different categories namely; innovation and learning ability, intellectual capital and finance. However, the effect of BI in relation to customer satisfaction (measured as the number complaints) was not established. In addition, various BI capability indicators in this study were not conceptualized. A study by Roodposhti and Mahmoodi (2012) established a robust correlation between economic values in firms with mature BI systems and their ROE/ROI. The findings also indicated that the association between ROE and basic financial parameters is lower in firms with low/medium use of BI when contrasted with firms with high use of BI. Nevertheless, the study did not take into consideration non financial measure like employee and customer satisfaction.

A quantitative study by Işık et al. (2013) on 92 respondents confirmed that quality of user access, flexibility, quality of data sources and flexibility had a significant and positive on the benefits firms derive from BI. The findings also confirmed risk management did not have a considerable impact on BI success. These results demonstrate that technological BI capability is essential. Hence, firms should ensure that these capabilities are fully implemented as they undertake BI deployment (Işık et al., 2013). Amini et al. (2021) conducted an empirical study to demonstrate BI's capability in the risk management of agricultural insurance policymakers in Iran. The findings show that the use of BI can dramatically reduce the inaccurate estimates attributed to uncertainties. Richard et al. (2014) concluded that research related to BI is still scanty, especially those that expressly explore the impact on firm performance. Melville et al. (2004) pointed out that there is still uncertainty on how IT contributed to firm's performance among the researchers hence, knowledge in this area stays untapped and uncoherent. Therefore, the study seeks to establish the effect of BI capability on firm performance. To explore this relationship, it is hypothesized that:

H_{01}: BI capability has no effect on firm's performance.

2.5 Business Intelligence, Complementary Resources and Firm Performance

Complementary resources consist of non-IT resources and wider organisational capabilities that help to realize value from IT investment and include culture, structure, organisation strategy and decision making process. They emerge as the synergic outcome between IT and other firm resources. Shollo (2013) conducted an empirical study to explore how BI output is used by decision-makers shape judgment and make organisational decisions. The longitudinal qualitative study was conducted on Danske Bank Group, an international financial institution with the head office in Scandinavia but present in 16 countries. The findings confirmed that BI output is utilised by business leaders to tackle illogicality in the organisation decisions and also to enhance legitimacy of their argument. However, the researcher assumed decision makers are always rational hence, limiting generalisation of the findings. Elbanna and Child (2007) observed that are there three dimensions to a decision process, that is political behaviour, intuition and rationality. For example, the authors argued that under political dimension, emergence of decisions stems from a process where decision makers goals differ, there's alliance formation to achieving the said goals and the most powerful person's goals and preferences take precedence irrespective of available information. Previous studies provide evidence of incidences where insights and excellent ideas have been turned down by firms, only to perform extremely well when implemented by other firms. For instance, the decision by Xerox's not to engage in the sale of computer hardware (Sharma et al., 2014). This study argues intricate organizational decision making processes are usually involved in generating options, assessing them and committing to a particular option hence, providing a moderating effect.

Previous studies done on information systems documented a positive effect between firm performance and organizational culture. For example, Rayat and Kelidbari (2017) conducted a case study on Iran's aviation industry on the effects of BI on organisation effectiveness. The results confirmed culture does have substantial influence on the effectiveness of BI. Further more, organisational effectiveness is aided BI. Just 13 out of 17 airlines participated in the study and hence, the result may not be reliable in drawing meaningful conclusion from the findings. Nevertheless, the results were consistent with the investigation of Arefin et al. (2015), who argued that the effectiveness of organisations is derived from BI systems and dependent on corporate culture. Sharma et al. (2014) reported that the individuals involved in decision making are sometimes limited by organizational norms that restrict the exploration of new ideas and can negatively affect the quality and acceptance of decisions, including the firm's capacity to carry out strategic decisions. Kulkarni et al. (2017) reported that the degree to which stakeholders in the organization embrace factual data in decision-making depends on the emphasis management place on evidence (as a routine) to support those decisions. Fink et al. (2017) assert that the business value of BI depends on the complementarily and compatibility with intended institutional routines through which learning generates new knowledge. An empirical study by Kulkarni et al. (2017) confirmed the mediating effect of top management. Based on data obtained from 486 corporates in six countries, top management enhances BI impact by: fostering and complying with analytical decisions, funding BI projects, investment in analytical skills and rewarding and acknowledging exemplars. However, data gathered for this study was skewed towards firms that had a high inclination to BI. Besides, other mediators such as culture were excluded from the study.

Organisation structure is one of the core pillars that constitute a congenial environment for business information systems success (Arefin et al., 2015; Brynjolfsson et al., 2011). Arefin et al. (2015) conducted an empirical study in Bangladesh and found that BI systems are more effective in influencing firm performance when there is a decentralized structure and rapid information relay to senior management. Data was collected from 225 firms and analyzed using SEM technique. However, collected data was from a single vendor of BI software, thus limiting the external validity of the findings. The connection between organisation strategy and BI effectiveness is apparent (Rayat & Kelidbari, 2017). Also, Trieu (2017) noted in his latest comprehensive review of literature that there is an absence of studies that evaluates the complementary connections between BI impacts and BI resources to help the organisation better comprehend the value creation process. BI system provides information to the top management and thus enabling them to make sound decision that have an impact on organisation performance. Hence, it is hypothesized that:

H_{02}: Complementary resources have no effect on the relationship between BI capability and firm's performance.

2.6 Business Intelligence, Organisational Capability and Firm Performance

Prior research by Kohli and Grover (2008) suggests that information management capability (IMC) that is enabled by IT leads to enhanced business capabilities, thereby affecting firm performance positively. IT investment serves as an accelerator of desired business capabilities. Therefore, Mithas et al. (2011) propounded a model involving two stages, information management capability as a primary construct and organisation capabilities made of higher-order capabilities (process management, performance management and customer management capabilities) as an intermediary between performance and BI. The researchers drew on a historical set of data from a consortium outfit with approximately 80 firms. The results confirmed that organizational capability has an impact on the relationship between information capability and firm performance. Furthermore, their study highlighted that the IMC has a greater impact on performance management capability, subsequently on process management and finally of customer management capability. However, the finding from this research cannot be generalized to firms globally. Data set was limited to firms within the group hence, enabling the researchers to manage the impact other parameters, for instance, culture.

Empirical evidence from research conducted by Ray, Muhanna and Barney (2005) in North America shows that shared information enabled by IT notably affects the capacity of the firm to obtain more customer intelligence and associated business processes with a final impact on business performance. The research employed a cross-sectional design and gathered information from 104 companies. The research setting was on a specific insurance industry with an exceptional spotlight on the customer process, thus generality of the study is limited. Firms undertake a set of actions in order to realize its strategic objectives hence, creating numerous avenues for the application of IT to streamline business operations (Melville et al., 2004). BI capability is a significant enabler of process capabilities by allowing organizations to develop analytical tools that create real time visibility of business processes, combination of processes and forewarn any decline in performance (Kalakota &Robinson, 2003). Likewise, in their survey-based study, Elbashir et al. (2008) discovered BI conveys benefits through improved business processes (business partner relations, inside procedure proficiency, and client insight benefits).

A survey study by Kim et al. (2011) in South Korea confirmed IT capability influence process oriented dynamic capability and subsequent impact on firm performance. It enables management to either enhance, adapt or restructure business process better than other competing firms in terms of consolidating business activities and reduction in cost. However, the study did not incorporate other factors (customer and performance management capability). Empirical study by Oliveira and Maçada (2017) demostrate the positive impact of IT capability on process performance, which in turn affects firm performance. The study was applied to a sample size of 150 large corporations in Brazil. IT capabilities were operationalized to include infrastructure, human, management and reconfiguration capabilities. In particular, positive impact was on firm profit when capabilities are applied in operational and production processes. However, this was a quantitative study, hence it does not sufficiently explain social realities. In line with the theoretical propositions in the IS capability theory, Mithas et al. (2011) posit that IS capabilities play a critical role in developing organisational capabilities. In turn, these capabilities favourably influence customer, financial, human resources, and organisational effectiveness (benchmarks of firm performance). This study seeks to contribute to the ongoing debate by focusing on the moderating role of organisational capability. It is hypothesized that:

H_{03}: Organisational capability has no effect on the relationship between BI capability and firm's performance.

2.7 Business Intelligence Capability, Organisational Capability, Complementary Resources and Firm Performance.

Mithas et al. (2011) devised a conceptual model connecting IS supported capability with organisational capabilities based on an empirical study conducted on a conglomerate group. 160 observations were collected from 77 companies spread across several sectors that include manufacturing, financial and hospitality. The findings from the study confirmed IS capability plays a significant part in the development of organizational capabilities. In turn, these capabilities favourably influence firm performance. However, the study did not address the other factors that moderate the relationship between BI and performance.

Elbashir et al. (2008) conducted an empirical study on 1873 managers from 612 organisations in Australia. Data collection was limited to conglomerate organisations that had embraced BI systems supplied by a single BI software vendor and used the technology actively for their business operations. The findings from the study established a direct BI impact at the operation level (on supplier relations, internal efficiency and customer intelligence) and indirect impact at organisational level. One of the major drawbacks of the study is the limitation to wider use of study results. While internal validity was guaranteed, external validity was compromised because data was obtained from users of BI software from one vendor. Vendors offer distinct capabilities for BI solutions. In addition, the study adopted perception based measures that are subjective to assess the impact at the process and organizational level. Finally, the researchers did not focus on other factors such as culture that moderate BI impact on performance.

Chen (2012) has argued that empirical BI related studies that expressly investigate the effect of BI and how other assets blend with BI to deliver superior returns are scarce. Consistent with aforementioned assertion, Elbashir et al. (2008) postulate that further research is required to explore factors that may mediate BI capability to performance such as culture. In contribution to the foregoing argument, Arefin et al. (2015) states that the role of organisational elements like structure, process, strategy, and culture on BI systems has largely gone unexplored. The study seeks to establish the combined effect of BI Capability, organizational capability, and complementary resources on firm performance. Hence, it is hypothesized that:

H_{04}: BI capability, organisational capability and complementary resources have no combined effect on firm performance.

2.8 Summary of Empirical Studies and Knowledge Gaps

The table below summarizes identified research gaps from previous studies on the same topic and how the current study seeks to fill the gaps.

Table 2.1 BI Research Gaps

Author	**Focus**	**Methodology**	**Findings**	**Knowledge Gap**	**Focus of the current study**
Fink, Yogev, and Even (2017)	BI and organisational learning; An empirical investigation of value learning processes	For exploratory analysis, qualitative approached was used while for confirmatory analysis, study was through cross sectional survey in Israel	BI stimulates benefits in the area of capabilities at operational and strategic levels. BI infrastructure and team positively affect these capabilities, but the relationship is moderated by exploitative and explorative learning	Save for optimisation of processes to create value, the proposed framework does not explicitly explain the path from BI capabilities to performance. The study does not adequately cover moderating and mediating variables	The study includes complementary resources as mediators. Organisational capabilities have been identified and added in consolidating the relationship between BI and performance

Arefin, Hoque, and Bao (2015	How BI affect the effectiveness of the organisation.	Survey, Bangladesh, South Asia (Quantitative research)	There's a positive effect brought about by BI on the effectiveness of the organisation having a tight fit between BI systems and structure, strategy, structure, process and culture	The study's sample drawn from a single BI software vendor hence, external validity is affected compared to when multiple vendors are chosen.	The study will target samples from multiple vendors in a local setting (Kenya).
Eybers (2015	Exploring the value of business intelligence using a second-generation balanced scorecard approach	A case study (qualitative approach), South Africa	BI inputs value to organisations in all four perspectives areas, namely the business value, user orientation, operational excellence and future orientation perspectives.	The study only focuses on measuring the impact of BI on performance but does not explain how this achieved. Sharma et al (2014) argues that BI impact requires deeper analysis more so on the role of decision making process and resource allocation.	Focus on measuring BI impact and adequately covers how BI capability impact organisation performance through intervening and moderating variables
Ida and Graeme (2015).	How business analytics systems provide benefits and contribution to firm performance.	Survey, Large US based organisation	BI capability contributes to firm performance in two pathways: directly by building a "single version of truth" and indirectly through CRM. CRM team and processes consume the insights generated by BI.	The study measures the benefits of information and the performance of the firm using managers' perception, which is subjective. Objective metrics of firm's performance could provide deeper insights and support study findings. Second, the study does not take into consideration other organisation capability such as process and performance management that have intervening effect on performance (Mithias et al 2011).	In measuring performance, financial measures such as return on investments and improved market share has been proposed making the results more objective. In addition, intervening variables such as process and performance management are included.
Buchana and Naicker (2014	The effect of mobile BI on organisational managerial decision making.	Survey, South Africa (Quantitative research.	Positive attitude by various stakeholders in the organisation leads to the actual use of the mobile business intelligence.	The research does not address the impact of decision made on the overall performance of the organisation.	Decision making process is incorporated as a moderating variable.

Richards et al. (2014)	Empirical study of BI impact on corporate performance management.	Survey from 337 senior managers, Canada (Quantitative research).	There's a direct influence by BI on the effectiveness of planning, analysis and measurements and indirectly influences operation effectiveness hence enabling organisation performance.	The study does not quantify the impact on organisation performance.	The impact on organisation performance to be quantified by gathering data on financial performance.
Yogev et al. (2013	How BI creates value	Survey, Israel	There's a contribution from BI to value addition by enhancing both operational and strategic processes of business.	The study takes a process approach to evaluate the impact of BI on organisation performance. The study ignores alternative approach that assumes BI is a product (Elbashir et al 2008, Popovic et al 2010).	The study fills the gap by considering other approaches by focusing on BI capabilities identified in section 2.4 above.
AL-Shubiri (2012).	Measuring the impact of BI on performance	Survey, 50 industrial firms listed on Amman stock exchange	BI plays crucial role to support decision-making (hence having an impact on performance) in all firms of all sizes more than learning and growth.	The study primary focus is in measuring the impact of BI but does not provide how this impact is achieved and the role of other moderating factors such as culture and structure.	The research looks at the mediating role of information capability as well as the moderating roles of organisational resources.
Mithas et el. (2011	How information management capability influences firm performance.	Case study, USA	Information management capability plays an important role in developing customer, process and performance management capabilities. In turn, these capabilities favourably influence firm performance.	The study did not include moderating factors such organisation leadership and structure. Secondly, the research was drawn from a single group hence external validity was not confirmed.	The study seeks to fill the gap by incorporating mediating factors. Survey design will be adopted to ensure both internal and external validity is addressed.

Hocevar and Jaklic (2010)	Assessing the benefits of business intelligence systems.	A case study (qualitative approach.	Qualitative methods such as a strategic analysis and the analysis of user subjective assessments are appropriate for evaluating investments in BI.	The study was based on the qualitative approach hence relying on user's perception that tend to be subjective.	In measuring BI the impact, quantitative is approach was also adopted.

Source: Author (2020)

2.9 Conceptual Framework

The conceptual model in Figure 2.3 was adopted from Mithas et al. (2011) framework. However, the conceptual model by Mithas et al. (2011) in Figure 2.2 only evaluated the indirect effect of information capability on firm performance through organisational capability (comprising process, customer and performance management capabilities).

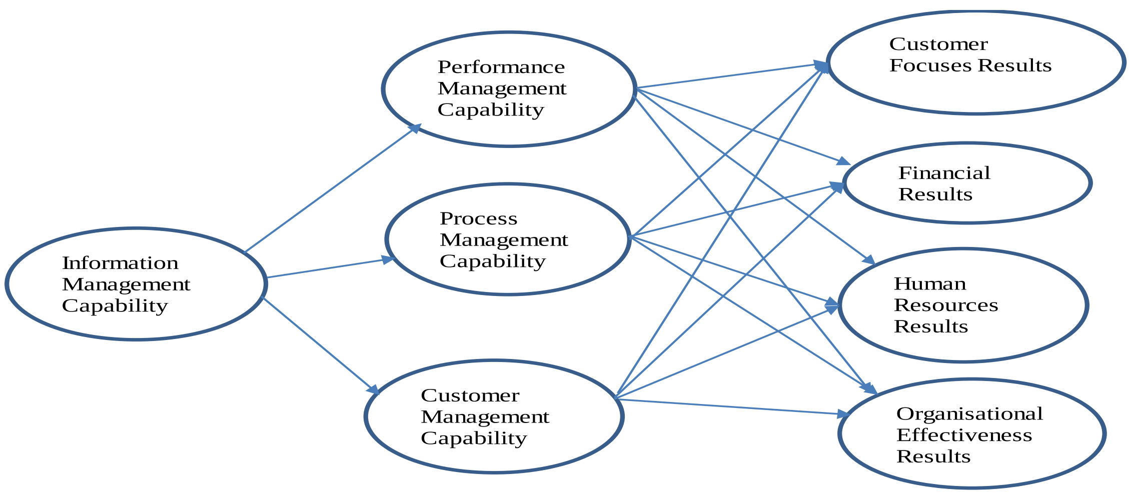

Figure 2.2 Conceptual Model by Mithas, Ramasubbu and Sambamurthy

Source: Mithas et al. (2011)

Hence, the model was modified to incorporate complementary resources presented in literature review, consisting of decision-making process, culture, structure and organisation strategy (Sharma et al., 2014; Arefin et al., 2015). The conceptual model also included specific BI capability dimension from Isik et al. (2013) and Peppard and Ward (2004). It schematically depicts the expected relationship among identified variables and their influence on firm performance. BI Capability is the independent variable and comprises quality of data source, data types, user access, data reliability, analytical capability, interaction capability, flexibility and IT skills. Firm performance is the dependent variable consisting of customer management, financial management, HR performance and organizational effectiveness. Complementary resources have a mediating effect on the link between BI capability and performance. It comprises decision making process, culture, structure and organization strategy. The framework also illustrates the moderating effect of organizational capabilities between BI capability and performance, consisting of customer, process and management capabilities.

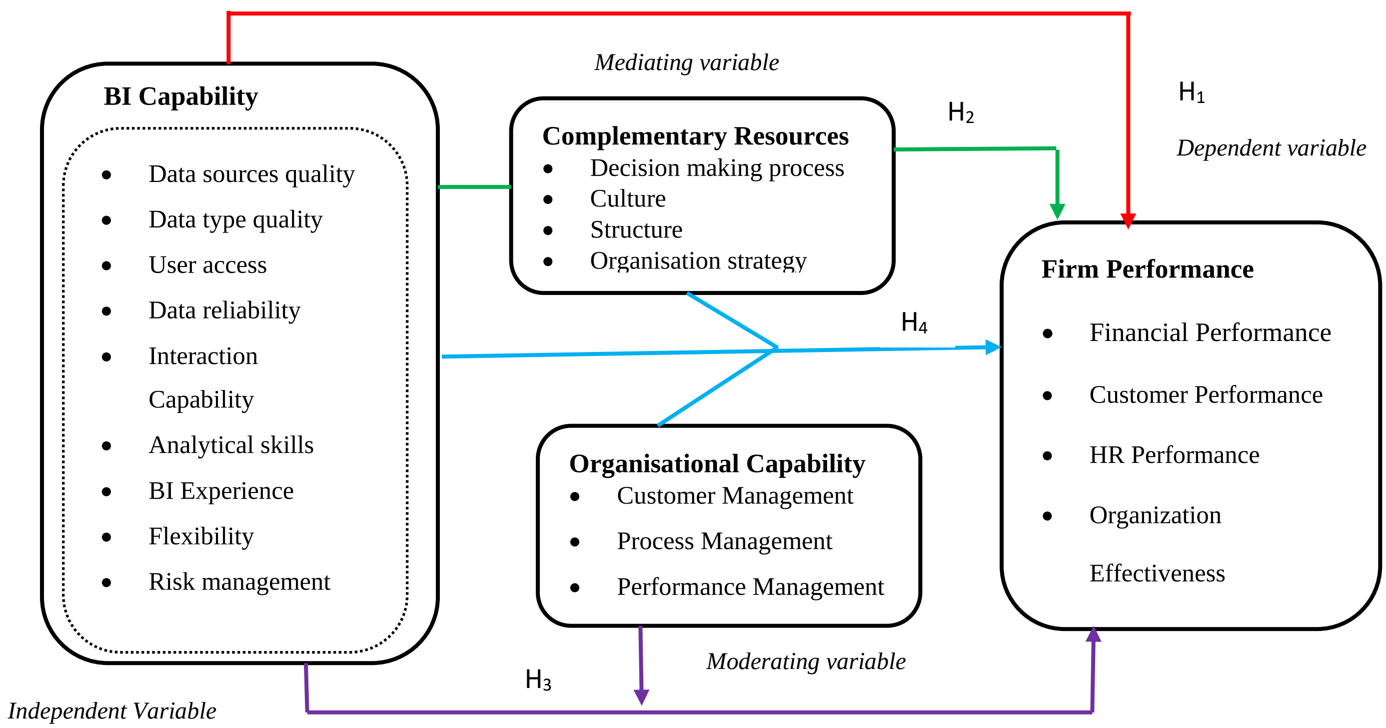

Figure 2.3 Conceptual Model

2.10 Research Hypothesis

The main aim of this research is to explain the impact of BI capability on performance of firms listed at the Nairobi Securities Exchange. Hence, four objectives were formulated as shown in section 1.3. The objectives are supported by the following four null hypotheses.

H_{01}: BI capability has no effect on firm's performance.

H_{02}: Complementary resources have no mediating effect on the relationship between BI capability and firm's performance.

H_{03}: Organisational capability has no moderating effect on the relationship between BI capability and firm's performance.

H_{04}: BI capability, organisational capability and complementary resources have no combined effect on firm's performance.

2.11 Chapter Summary

The chapter presented empirical and theoretical review of BI impact on performance. The review was guided by information system capability theory, Knowledge based theory and Organisation learning theory. Application of these theoretical perspectives to the study was addressed intensively. The relationship between identified key variables (BI capability, organisational capabilities, complementary resources and firm performance) was highlighted in reference to previous studies. Summary of empirical studies and the knowledge gaps, including how the study attempts to fill identified gaps was also presented. Finally, conceptual framework, including research hypotheses was also presented.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents the research methodology. The chapter outlines philosophical tenets that the study is anchored. It also covers the research design, data collection, target population, validity and reliability of measurement scales, operational definition and measurement of variables and data analysis techniques.

3.2 Research Philosophy

The research paradigm (also referred to as worldview, epistemologies and ontologies or broadly conceived research methodologies) offers a framework within which research is carried out Creswell (2014). Adopted philosophy in a study is mainly influenced by the particular view of researchers on the relationship between knowledge and the process through which it is developed (Saunders, Lewis & Thornhill, 2009). The type of believe held by individual researchers results in choosing either qualitative, quantitative or mixed methods approach. There are two central approaches to philosophies (in social science research) that inform knowledge generation; ontology and epistemology. The assumptions determine the philosophy preferred by a researcher.

Ontology tackles the questions concerning "what is the nature of reality". Two schools of thought, objectivism and subjectivism, attempts to handle this question (Saunders et al., 2009). According to an objectivist view of ontology, social entities exist wholly independent of social actors taking an interest in their existence, and the analyst has no influence at all. The subjectivist view of ontology suggests social phenomena are generated from social actors' opinions and resulting actions. Epistemology is the branch of philosophy that focuses on the nature, possibility, scope, and general rationale of knowledge. It is all about how we gain knowledge and different ways of gaining that knowledge. Researchers ask questions in epistemology such as ' What do you know?, and ‘How do you know?. Epistemology concerns what in an area of study embodies admissible knowledge (Saunders et al., 2009). There are three main philosophical views that have greatly guided most social science research; positivism, interpretivism (constructivism) and pragmatism.

3.2.1 Positivist approach

The positivist worldview presupposes reality that is objective and can be estimated through empirical evidence (Neuman, 2014). Thus, the problem examined by positivists dependably mirrors the need to distinguish and survey the reason that impact results. Learnings that develop through this worldview depends on cautious perception and estimation of the objective reality Creswell (2014). The role of the researcher in positivism studies is limited to data collection and interpretation. It is assumed that the researcher is independent of the research subject and does not affect or influenced by subject of the study (Saunders et al., 2009). In positivism, the study is based on a theory, previous studies outcomes, individual observations followed by hypothesis formulation. Following the formulation of the hypothesis, data is collected and analyzed to either support the hypothesis or rejects it, leading to the further development of theory, which then may be tested by further research.

Positivism is biased towards the use of quantitative perspective. While positivism has gained prominence in social research, it is not without criticism, more so on its definition of objectivity. Cohen, Manion and Morrison (2007) differs that positivism gives us the clearest conceivable perfect knowledge. Regardless of how stringently a researcher cling to the scientific techniques, there will never be a result that is objective. This position overlooks the truth that a great deal of human choices are made during the time spent directing the study. Moreover, researchers are themselves individuals from a social setting slanted to subjectivism. For example, in picking the research topic, devising instruments to be utilized in research, selecting alpha levels and interpreting the research findings (Johnson & Onwuegbuzie, 2004).

3.2.2 Interpretivist Approach

The interpretive approach emerged to address the issues arising from using a positivist paradigm. The world of social business and management is sophisticated to hypothesize in comparison to physical sciences. Interpretivism approach affirms that knowledge is subjective based on experience from perspectives of individuals. According to Saunders et al. (2009), the focus of phenomenology is individual interpretations, personal knowledge and instant experience. Scholars who subscribe to this approach make assumption that only biased interpretation and involvement in real life would facilitate the researcher in understanding the phenomenon better. It inspires use of qualitative viewpoint in which perception is used to make sense of the world by humans. Creswell (2014) asserts that the intention of the researcher is to make sense of (or interpret) the meanings of the world that others have. Instead of beginning with a theory (as in positivism), inquirers inductively develop a theory or pattern of meaning.

Interpretive research presents a unique set of challenges also. First, in data collection and analytical efforts, it’s time-consuming and resource-intensive than positivist research. Insufficient data can lead to false or premature assumptions. On the contrary, the researcher may not process too much data effectively. The approach also necessitates competent researchers capable of seeing and interpreting complicated social phenomena from the perspectives of encapsulated respondents and aligning the diverse views of these participants without introducing their personal preconceptions (Creswell, 2014). However, in the case of business and management research, this perspective is highly appropriate, especially in areas such as organizational behaviour, marketing and human resource management. Business situations tend to be not only complex, but also unique as well (Saunders et al., 2009). It is composed of a specific set of circumstances and people at a particular time.

3.2.3 Pragmatism Philosophy

Pragmatism attempts to find a common position where both positivism and interpretivism are accommodated, hence it was adopted for this research. The ultimate goal is not to substitute either stance, but to draw and mitigate the shortcoming of both approaches in a single study. Johnson and Onwuegbuzie (2004) affirm that modern age research is becoming increasingly interdisciplinary, complex and dynamic; hence, to generate superior research, selected approach should be complemented. Mingers (2001) asserts that multiple paradigms are considered necessary in IS research to gain a complete understanding of a social phenomenon. The author grouped research methods in terms of their connection to the three worlds that include the material world, the social world, and the personal world. Each domain has distinct epistemological options. The physical realm is external and unrelated to humans. Our connection with this realm is based on observation (instead of experience or participation). It can be classified as objective. The personal world is the world of one's own thoughts, feelings, experiences, and beliefs. It's not observed, but experienced. This world is subjective. There is the social world that we share and partake in. Our connection to it is inter-subjectivity. Hence, using only one method, one often only gains a limited view of a particular situation of research. The current problem of this study and associated objectives are multifaceted, therefore, cannot be addressed by positivism or interpretivism alone. The research took a paradigmatic stance to understand BI's impact on performance, taking into account the moderating effect of organizational factors and the mediating effect of complementary resources.

3.3 Research Design

Research design refers to the overall strategy to integrate the study's different components, including expression of casual relationships between variables. It is the roadmap for collecting, measuring and analysing data (Saunders et al., 2009). This study used a cross-sectional mixed methods design. Cross-sectional survey involves collecting data at a particular time point across different members in a population (Neuman, 2014). The design permits the researcher to offer description to the variable of interest in the study. Besides, it allows for hypothesis testing to determine the relationship between two or more variables at a given point in time (Bryman, 2012). Cross-sectional survey design is associated with deductive approach which seeks to explain causal relationships among identified variables. This design was used by Yogev et al. (2013), among other researchers and enabled them to test hypotheses and draw conclusions on a related study.

The study was guided by mixed method approach that involves combining elements of qualitative and quantitative approaches (Johnson et al., 2007). Mixed methods in IS research have recently begun to receive attention due to the benefits associated with this approach (Yu & Khazanchi, 2017). The benefits include the ability to harness the strength of different methods, provides deeper insights into phenomena that are enigmatic when only using quantitative or qualitative methods, tackle research issues involving real-life understanding of the context, multi-level view and influence of culture ((Johnson & Onwuegbuzie, 2004; Yu & Khazanchi, 2017; Johnson, Onwuegbuzie & Turner, 2007). It is significantly useful in situations where existing theories and research results do not fully describe understanding of a phenomenon under consideration by addressing a number of confirmatory and explanatory questions at the same time ((Johnson & Onwuegbuzie, 2004).

According to Venkatesh, Brown & Bala (2013), this approach is helpful where existing research is fragmented, incomplete and equivocal. The authors clearly state:
"If IS researchers continue to publish single method papers from mixed methods programs, they are likely to miss the opportunity to discover, develop, or extend a substantive theory in richer ways than possible with single method papers. A mixed methods approach, particularly the associated meta-inferences, offers mechanisms for discovering substantive theory by allowing researchers to not only unearth components related to a phenomenon, but also unveil interrelations among these components and boundary conditions surrounding these interrelations…. Thus, publishing single method papers from mixed methods research programs is disadvantageous to a researcher and the academic community" (Venkatesh et al., 2013, p.31).

Mixed methods approach was adopted to mitigate the weakness of qualitative and quantitative approaches (Yu & Khazanchi,2017). Creswell and Clark (2011) opined that a researcher must make four critical decisions that eventually define the mixed method design to be adopted in the investigation. The four key decisions include the degree of interaction between the strands, strands priority, timing of the strands and the procedure for mixing the strands. Table 3.1 describes in detail these choices and the options selected for this study.

Table 3. 2 Critical decisions in selecting a mixed method design.

Key Decision	**Description**	**Option selected for this study**
Level of interaction	Refer to the degree of independence or interplay between the two strands.	**Independent.** Qualitative and quantitative research questions (appendix 1 & 2), data collection and data analysis were handled separately. However, the results were combined during interpretation stage.
Priority of qualitative and quantitative strands	The relative significance or weighting of both strands in the answer to research questions. There are three possible weighting options; equal priority, quantitative priority and qualitative priority.	**Equal priority**. The two strands were accorded equal weighting in dressing research problem.
Determining the timing of qualitative and quantitative strands	Refer to the time of collecting data sets and can be classified in three ways: sequential, concurrent, or multiphase combination.	**Concurrent timing**. Both qualitative and quantitative strands were carried out in a single phase of the research.
Determining where and how to mix the quantitative and qualitative strands	Refers to linking of qualitative and quantitative strands of the study. The mixing strategies include (a) mixing during interpretation, (b) mixing during data analysis, (c) mixing during data collection, and (d) mixing at the level of design.	**Mixing during interpretation.** Combination of output from two strands commenced after analysis of the data sets. Conclusions of this study reflected what was learned from integrating results from the two strands.

Source: Adopted from Creswell and Clark (2011)

Creswell and Clark (2011) recommended six major mixed methods designs that reflect the above key decisions; the convergent parallel design, the explanatory sequential design, the exploratory sequential design, the embedded design, the transformative design and the multiphase design. The study adopted convergent parallel design (also referred to as triangulation design) to obtain different but complementary data to best understand the impact of BI on performance. The design was employed in order to directly compare quantitative and qualitative evidence to authenticate results and also to detect inconsistencies between the two forms of data (Plano Clark et al., 2008). Furthermore, the design was selected due to the relatively short data collection duration, in contrast with other mixed methods designs (Creswell & Clark, 2007). Triangulation design/convergent parallel design is the oldest and also the most distinctive form of mixed methods research (Creswell, 2014). As depicted in Figure 3.1, quantitative data and qualitative data was concurrently gathered but analysed individually. The findings were eventually merged at interpretation stage, giving equal emphasis to both forms of data. This approach permits enrichment of findings in a single study (Creswell & Clark, 2011). The next section provides a thorough account of the approaches used in this study starting with quantitative strand.

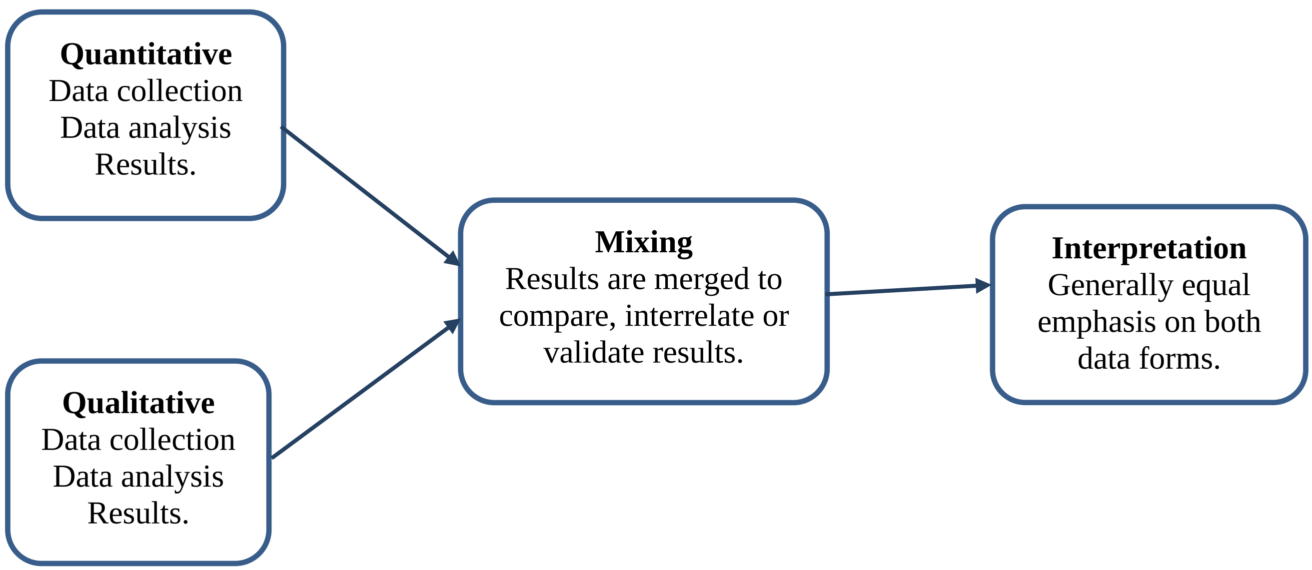

Figure 3. 1 Triangulation design

Source: Creswell & Clark, 2007

3.4 Quantitative Strand of the Study

3.4.1 Justification for Using Quantitative Approach

In a scenario where the investigator wishes to study how a given variable affects another variable of concern, quantitative research technique is a preferred option according to Creswell (2014). In utilizing this technique, the researcher begins with setting out a hypothesis, gather data to either bolster or negate the hypothesis, make modification, or perform further tests. Basias and Pollalis (2018) ascertains that the technique is widely used when huge volumes of quantitative information need to be analysed to confirm and test a hypothesis, there is uncertainty about the theories being considered, a questionnaire is used to collect data and gathered data can be quantified. The focus in this research is on BI's effect on firm performance measures (financial, client, human resources, and efficiency of an organisation). Hence, quantitative data was gathered in order to test the four hypotheses outlined in chapter 2.

In selecting this approach, the research was guided by the benefits enumerated by Johnson and Onwuegbuzie (2004). First, the technique enables the researcher to demonstrate the correlation between the variables identified in the literature review in chapter 2. Second, it draws conclusions from a large number of participants; hence, the results can be generalized. Finally, the technique also employs efficient tools for data analysis in addition to examining probable cause and effect among the variables.

3.4.2 Population of the Study

The target population of the study was all firms listed at the Nairobi Securities Exchange (NSE) as at 31st December 2018. These organizations represent vital sectors of the Kenyan economy, in particular, agriculture, automobile and accessories, banking, commercial and services, construction and allied, energy and petroleum, insurance, investments, telecommunication and technology (Nairobi Securities Exchange, 2018).

The choice of listed companies for the study is justified by the availability of objective and reliable economic/financial performance data having invested in Information Systems (IS). The investment is partly driven by Foreign Direct Investment (DFI) that influences firms to adopt best practices through technology transfer. Stringent reporting requirements by Capital Markets Authority (CMA) through a well laid down regulatory framework targeted at promoting market integrity, is compelling firms to increasingly consume vast amount of data hence, the drive to invest in BI Systems. In addition, performance data is also reviewed and authenticated annually by the leading external auditing firms.

3.4.3 Data Collection

Data was collected using a structured questionnaire (Appendix 1) tailored to address identified study objectives. This method has several advantages; efficiency in data collection, convenient to respondents and eliminates interviewer variability (Bryman, 2012). To simplify the process of coding and analysis, closed ended questions were used. The instrument was refined by incorporating input form supervisors and feedback from the pilot study. The first section focused on obtaining respondent's demographic information. Section two centered on gathering data relating to BI capability while section three was designed to capture the data on organisational capabilities. Section four focused on complementary resources and lastly, section five was essential in compiling data relating to firm performance.

The unit of analysis was listed firms. Data was collected from management staff such IT Manager/Chief information Officer and Finance Manager/Finance Director in each firm. This is because they are considered to be key informants with information on study objectives (Kim et al., 2011). According to Hambrick's (2007) upper echelon theory, top management shapes organisational performance and is thus best suited for this study. A five-point Likert scale with items ranging from '1= not at all' to '5 = very large extent' was selected to prepare questionnaire items. Literature indicates that a five-point scale is less confusing (Aydiner et al., (2019). A total of 63 questionnaires was administered through drop and pick method. To ensure this approach was effective, a personal letter of introduction was attached explaining purpose of the study and assuring of confidentiality and privacy. The respondents were also provided with the researcher's contact information (that is, telephone number and e-mail address) to enable them to make relevant inquiries.

3.4.4 Operationalization of the Variables

The four latent variables as set out in section 2.8, were operationalized in reference to previous studies and expert opinion to ensure construct validity. Operationalisation defines variables into measurable factors. In this study, all four variables used several measures to incorporate latent variables' multidimensionality. Table 3.2 summarizes the operationalisation of study variables.

Three dimensions of BI capability were captured in this study; technical, human capital and organisational dimension. Technical dimension was operationalized by quality of data sources, data type quality, user access, reliability and interaction capability. It was assessed by 42 items adopted from Isık et al. (2013) and Ida & Graeme (2015) on a five-point Likert scale. Human capital was operationalized by analytical skills and BI experience. It was measured by eleven items adopted from Isık et al. (2013). Under organisational dimension, participants were requested to state how far the application in use is flexible and provide risk support to management as adopted from Isık et al. (2013) and Xu & Kim (2014).

Complementary resources were operationalized by structure, culture, decision making process and organisational strategy. Structure and cultured were measured by eight items on a five-point Likert adopted from Arefinet et el. (2015). Decision making process was assessed by ten items adopted from Elbana and Child (2007) designed to capture the process of making choices to single out the best alternative. Organisational strategy was evaluated by seven items adopted from Arefinet et el. (2015). Respondents were asked to give feedback on how the organisation was achieving its goals by interacting with external environment.

Organisational capability was operationalized by process, customer and management capabilities. Process management capability was assessed by three items on a five-point Likert scale measuring the extent to which firm use BI output improves efficiency of internal process and staff productivity. The items were adopted from Elbashir et al. (2008). Customer management capability was assessed to determine the extent to which the application is used to manage customers expectation and preference by four items adopted from Ida & Graeme (2015) and Mithas et al (2011). Performance management capability was measured by three items on a five-point Likert scale designed to evaluate the use of BI in gathering and monitoring key performance indicators across the business. The measures were adopted from Mithas et al.(2011).

The dependent variable in this study is firm performance. The study adopted Malcom Baldrige National Quality Award (MBNQA) framework, which explicitly tests IT-enabled information flows (Ghosh et al., 2003) to operationalize this construct. The framework identifies four dimensions of firm performance used in this study and include human resource, customer-focus, financial, and organisational effectiveness. Participants were requested to specify the degree to which their organisations had attained these four dimensions of performance by using BI application. The identified dimensions were measured by 20 items on a five-point Likert scale adopted from Lee and Choi (2003) and Mithas et al, (2011).

Table 3. 2 Operationalization of Study Variables

Variable	Operational definition	Indicator	Questions	Measurement scale	Ref
BI Capability (**BC**)	Data type quality (**DTQ**)	Extend to which BI provides accurate, comprehensive, consistence and high quality qualitative and quantitative data	2 (2A-2H)	Interval Scale.	Isık et al. (2013), Ida & Graeme, (2015)
	Data sources quality **(DSQ)**	The extend of internal and external data sources being available, usable and easy to understand	2 (1A-1G)	Interval Scale.	Isık et al. (2013), Ida & Graeme, (2015)
	User access (**UA**)	Ability to link to all required information	2 (4A-4E)	Interval Scale.	Isık et al. (2013), Ida & Graeme, (2015)
	Reliability of data (**RD**)	Data gathered from internal/external source reliable and updated regularly.	2 (3A-3H)	Interval Scale.	Isık et al. (2013), Ida & Graeme, (2015)
	Interaction capability **(IC)**	Ability to easily access data from other systems and applications	2 (6A-6C)	Interval Scale.	Isık et al. (2013), Ida & Graeme, (2015)
	BI experience (**BE**)	users are knowledgeable and share own experiences on the use if BI	2 (9A-9D)	Interval Scale.	Isık et al. (2013)
	Analytical skills (**AS**)	Extent to which BI system provides a variety of business analytical tools to analyze the data	2 (5A-5B)	Interval Scale.	Isık et al. (2013)
	Flexibility (**FL**)	BI scalability with regards to transactions and changes in business requirement	2 (7A-7D)	Interval Scale	Isık et al. (2013) Xu & Kim, 2014
	Risk management support (**RS**)	The extent to which BI assist in reducing uncertainties in the process making decision	2 (8A-8C)	Interval Scale.	Isık et al. (2013) Xu & Kim, 2014
	Customer management capability (**CMC**)	Ability to determine requirements, expectation & preference of customers. Acquisition, satisfaction and retention of customers.	3 (CC 1-CC4)	Interval Scale.	Ida & Graeme, (2015); Mithas et al, (2011

Organisational Management Capability (**OC**)	Process management capability (**PRC**)	Reduced operation cost, improved efficiency of internal processes and increased staff productivity	3 (PR 5-PR7)	Interval Scale.	Elbashir et al (2008)
	Performance management capability (**PMC**)	Ability to gather and monitor KPIs, the ability to connect measurement system with decision making, feedback to stakeholder on performance	3 (PM8-PM10)	Interval Scale.	Mithas et al. (2011)
Complementary resources (**CR**)	Structure (**ST**)	Task division for the purpose of efficiency and clarity.	4 (CS 1-4)	Interval Scale.	Arefinet et el, (2015)
	Culture (**CU**)	Shared values and beliefs that shape behavioural norms	4 (CO 1-4)	Interval Scale.	Arefinet et el, (2015)
	Decision making process (**DM**)	Political behaviour (DP1) Intuition (DP2) and Rationality (DP3)	4 (DP1-A to DP3-C)	Interval Scale.	Elbana & Child (2007)
	Organisation strategy	Analysis, defensiveness, futurity and proactiveness	4(CH8 - 12)	Interval Scale.	Arefinet et el, (2015)
Firm performance (**FMP**)	Financial performance (**FP**)	• Sales growth- Increase in revenue, • Return on investments- Earning generated from invested capital • Asset utilization index- Revenue generated expressed as a percentage of total assets	5 (FP1-3) Section F	Ratio/Interval scale Ratio/Interval scale Ratio/Interval	Mithas et al. (2011)
	Customer performance (**CP**)	Extent to which customer complaints have dropped and loyalty has improved. Growth in customer base.	5 (CP4-5)	Interval Scale.	Mithas et al. (2011)
	HR performance (**HP**)	Extent to which employee satisfied, developed, demonstrate exceptional performance and retained.	5 (FP8-9)	Interval Scale.	Lee & Choi (2003) Mithas et al. (2011)
	Organisational effectiveness (**OE**)	Demonstrated, innovation, efficiency in work processes, cost reduction and improved coordination with partners	5 (FP10-13)	Interval Scale.	Lee & Choi (2003 Mithas et al.(2011)

3.4.5 Pilot Testing

Bryman (2012) echoed the need to undertake a pilot study prior to issuing self-completion questionnaire to ensure that the research instrument is working well. Hence, pilot study was undertaken to identify the adequacy of guidelines for participants, ensure questions are flowing well and phrasing of words is correct, ensure questions wording is correct, request feedback from respondents to identify issues of ambiguity and complexity and finally to assess whether each query provides a sufficient variety of opinions. Yin (2009) noted that the selection of a pilot case can be premised on convenience, accessibility and geographical proximity. Consequently, firms located in Nairobi were targeted. Furthermore, extent literature as noted by Connelly (2008) posit that a pilot study should represent at least 10 percent of the larger research project. Therefore, seven firms not listed on NSE we selected to pretest the questionnaire (10% of 64). Two participants found certain questions difficult to answer with respect to the feedback received, but instructions were clear. However, while performing the pilot study, there were certain difficulties experienced, for instance, one manager was so busy that the researcher had to visit the firm several times to collect the questionnaire. Largely, most of the feedback received related to definition of terms used and flow of questions. The feedback was reviewed and necessary revisions to the questionnaire done before roll out.

3.4.6 Quantitative Data Analysis

Before analysing collected data, it was cleaned to ensure missing values, suspicious response patterns and outliers are identified and contained (Hair et al., 2017). Meaningful output from data analysis is subject to quality of data screening. Bryman (2012) posit that missing data occur due to hardware failure, missed appointments and non-response, either intentionally or unknowingly to some items. Missing values of less than 5% of the total data set is not significant (Kline, 2015). The researcher inspected the questionnaires presented to guarantee adequate completion. Before undertaking the analysis, negative items in the questionnaire were reverse coded. A preliminary descriptive statistic was computed after capturing the data in SPSS to detect the incidences of missing values. No direct data entry is provided by SmartPLS. SPSS was therefore used and subsequently transferred in csv file format to SmartPLS. The mean substitution method was used in resolving missing data. This method was adopted because it is simple to perform and time efficient (Abdulwahab, Dahalin & Galadima, 2011). The next step was the assessment of outliers. Outliers are any numerically remote observations compared to the rest of the data.

Kline (2015) assets that outliers are values that exceed three standard deviations above the mean.

Although PLS-SEM is a non-parametric statistical method, suggesting that it does not require the data to be distributed normally (Hair et al., 2014). However, data that is too far from normal is inappropriate in the parameter assessment. Nonnormal data specifically inflates standard error generated from bootstrapping. Hair et al. (2017) recommended skewness and kurtosis measures to be used to examine data distribution. Hence, the measures were adopted in this study. Skewness evaluates to what extent the distribution of a variable is symmetrical. If the distribution for a variable extends to the right or left tail of the distribution, the distribution is defined as skewed. Skewness is demonstrated when the output generated is higher than +1 or smaller than –1. The overall guideline for kurtosis is that if the amount exceeds +1, the distribution is too peaked. Distributions that exhibit skewness and/or kurtosis that go beyond these rules are regarded as non-normal (Hair et al., 2017). Finally, the researcher applied the Structural Equation Modelling (SEM) analytical technique to further analyse the data. SEM was used to assess the measurement model, confirm the model's fit and check the convergent and discriminating validity of the constructs.

3.4.7 Structural Equation Model

Structural Equation Modelling (SEM) is a second-generation multivariate data analysis tool (Hair et al., 2017) used in testing latent variables, including their interrelationships (Hair et at., 2014). Multivariate analysis comprises the use of statistical methods that evaluate several variables concurrently. Although the use of SEM as a statistical instrument for evaluating theoretical and conceptual models and/or testing empirical relationships was originally created for use in genetics, it has acquired momentum and popularity in other fields (Shanmugam & Marsh, 2015). It is an offspring of multiple regressions and permits the identification of exogenous and endogenous in the same model. According to Bagozzi and Yi (2012), SEM can evaluate multiple variables and their connections in a single comprehensive run. It also allows the researcher to model the interrelations in both manifest and latent constructs. Furthermore, it is possible to take into account types of errors bedeviling first generation procedures. For example, it is possible to explicitly model and estimate random or measurement errors in indicators of latent variables (Bagozzi & Yi, 2012).

SEM was used in this research project for the following reasons. First, social science data often contains a considerable amount of measurement errors. In contrast to first generation instruments, SEM takes into account measurement errors by explicitly including measurement error term corresponding to observed variable. Consequently, findings about construct relationships are not biased by measurement errors (Shanmugam & Marsh, 2015). Second, Social science theories often refer to variables that cannot be observed directly (constructs). Hence, several indicators are selected to operationalise identified construct because an ideal operationalisation cannot be provided by a single measure. SEM enables simultaneous use of multiple indicators per construct, leading to more valid construct findings (Bagozzi & Yi, 2012). Finally, SEM also enables the modeling and testing of complicated relationship patterns, including a variety of hypotheses concurrently (Urbach & Ahlemann, 2010). This would often involve several and distinct analyses using first generation tools. SEM offers a wide, integrative feature that transmits synergy and complementarity between various statistical methods (Bagozzi & Yi, 2012). Hooper, Coughlan and Mullen (2008) urged that this technique has become a choice for many researchers across social science fraternity.

There are two primary approaches to SEM, that is Partial Least Square SEM (PLS-SEM) and covariance-based SEM (CB-SEM) (Astrachan, Patel & Wanzenried, 2014). They are two distinct methods that focus on the assessment of cause and effect relationships between latent variables but vary in their fundamental assumption and assessment processes. CB-SEM is commonly used in social sciences leveraging on software packages such as AMOS and LISREL. CB-SEM has two main goals; to demonstrate the patterns of covariance among a set of manifest variables (indicators), and to give an explanation for as much of that variance as possible within a specific research model. According to Hair at el. (2014), CB-SEM is a preferred technique of data analysis to confirm or reject theories through hypothesis testing, especially when the sample size is big, data is distributed normally and the model is defined properly. However, Hair at el. (2017), observed that it is often hard to locate evidence that satisfies highlighted requirement.

PLS-SEM tends to focus on variance analysis and can be performed with PLS-Graph, VisualPLS, SmartPLS and WarpPLS (Wong, 2013). Unlike CB-SEM, which follows maximum likelihood (ML) estimation procedure, PLS-SEM utilizes a regression-based ordinary least squares (OLS) estimation technique to explain the variance of latent constructs (Astrachan et al., 2014; Hair et al., 2011). Wong (2013) observed that PLS-SEM is a simple modeling approach that has no data distribution assumptions and has been implemented in many areas, including business strategy and information management systems. Wong (2013, p.117) further stated that "*PLS-SEM analyses can easily incorporate single-item measures, and can obtain solutions from much more highly complex models, that is models with a large number of constructs, indicators and structural relationships"*. Hair, Ringle and Sarstedt (2011) described it as a "silver bullet" in research. The study adopted PLS-SEM. PLS-SEM is an appropriate tool explaining changes in key construct caused by other constructs. It also has the additional benefit of being able to work with a small sample size (Hair et al., 2014). The study targeted 63 respondents. This approach also enables flexible handling of a model with more elements such as moderating and mediating constructs, nonlinear relationships or hierarchical component models. Hair et al. (2017) posit that "if correctly applied, PLS-SEM indeed can be a silver bullet in many research situations". To analye the data, SmartPLS version 3.0 was used. The software enables computation of standard regression weights between constructs, indicator reliability through factor loadings and correlation coefficients to explain the proportion variance between constructs. SmartPLS also offers significant testing capabilities. T-statistics can be produced to determine the level of statistical significance among constructs and thereby facilitating mediation testing.

3.4.8 Reflective models and Formative models

In structural equation modeling, there are two kinds of measurement scale ; formative or reflective (Wong, 2013). In a reflective model, causal arrows in the path originate from the latent construct towards the observed items (Wong, 2013). The model in this study is reflective. Previous studies on a similar topic such as Kim et al. (2011), conceptualized indicators for IT capability as reflective. For example, the latent variable organization dimension (OD), in the current study consists of two indicators, flexibility (FL) and risk management support (RS). Reflective indices represent all possible elements within the construct's conceptual domain. Considering that all indicator objects are triggered by the same construct (i.e., they originate from the same domain), indicators connected with a specific construct should be extremely correlated (Hair et al., 2014; Bagozzi & Yi, 2012). Given that relationships span from constructs to indicators, a shift in latent characteristics will alter indicators simultaneously. Hair et al. (2014) observed that reflective indicators are connected to a construct through loadings hence, the need to verify the reliability and validity of the outer model. Reliability is evaluated by estimating construct internal reliability while validity is determined by convergent and discriminant tests (Hair, Ringle & Sarstedt, 2011).

In a formative model, causal arrows in the path originate from indicators (observed items) towards latent construct (Wong, 2013). A notable feature of these models is that indicators cannot be interchanged because each indicator captures a particular aspect of the construct (Hair et al. (2014). For example, indicators such as divorce and car accident are utilized as a measurement of employee stress level. However, car accident has no correlation with divorce, but they jointly determine stress level. Wong (2013) asserts that when using a formative measurement scale, it is not mandatory to report reliability of indicators, internal consistency reliability and discriminating validity. The author argues that since a latent variable consists of uncorrelated measures, computing, outer loadings, composite reliability and the square root of average variance extracted (AVE) are irrelevant. Hair et al. (2011) contend that formative indicators do not contain errors thus statistical assessment metrics for reflective models cannot be shifted to formative models. Nevertheless, Hair et al. (2011) pointed out theoretical rationale and expert opinion is used to assess formative models.

Figure 3.2 below demonstrates the main distinction between the two approaches. The gray circles show the scope of each indicator as depicted by Hair et al. (2014). Whilst the strategy to reflective measurement seeks to maximize overlap among interchangeable indicators, formative measurement strategy attempts to minimize the overlap.

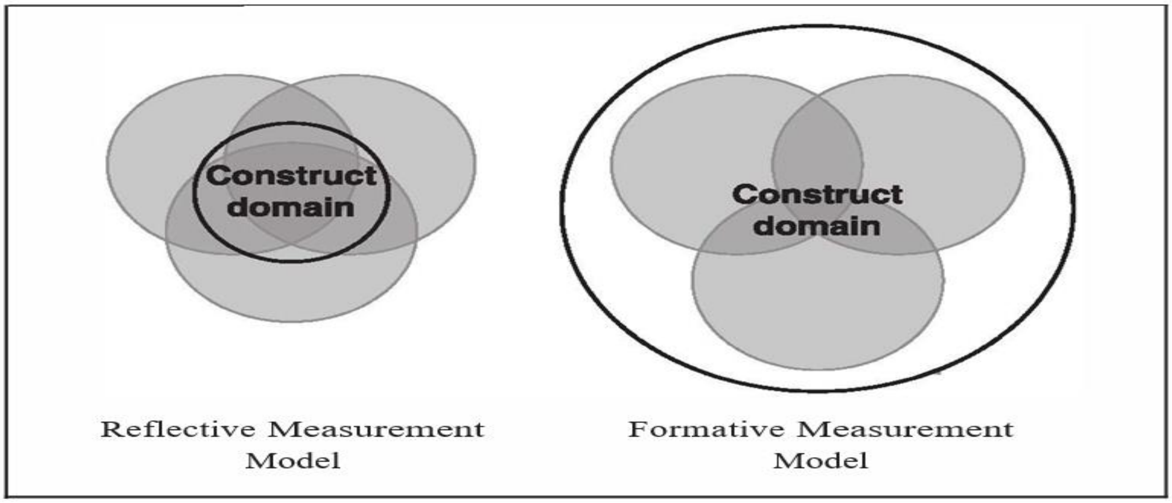

Figure 3. 2 Difference between formative and reflective measures

Source: Hair et al. (2014).

3.4.10 Model characteristics

The structural equation model has two sub-models: outer and inner models (Wong, 2013), as shown in Figure 3.3 below. The inner model (also known as the structural model) stipulates the connection between independent and dependent latent variables. Wong (2013) posits that variables under inner model can be either exogenous or endogenous. An exogenous variable has outward path arrows, and none leads to it (Garson, 2016). An endogenous variable has at least one route leading to it and reflects other variable(s) impacts. The outer model (also known as the measurement model) establishes the latent variables relationship with their observed indicators. Observed indicators can be evaluated directly and serve as indicators for a latent variable. Figure 3.3 represent the relationship between inner and outer model.

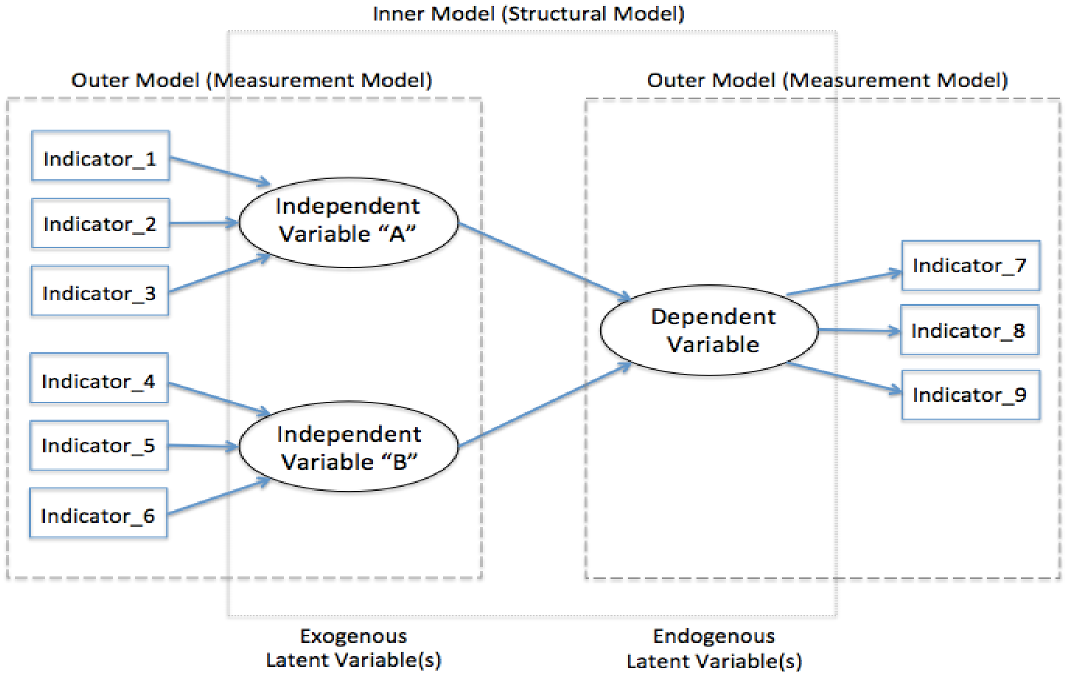

Figure 3. 3 Inner vs outer model diagram

Source: Wong (2013).

Figure 3.4 below shows the hypothesised structural model based on the constructs related to BI capability as the independent variable, organizational capabilities as the moderating variable, complementary resources is the mediator variable and the dependent variable is firm performance.

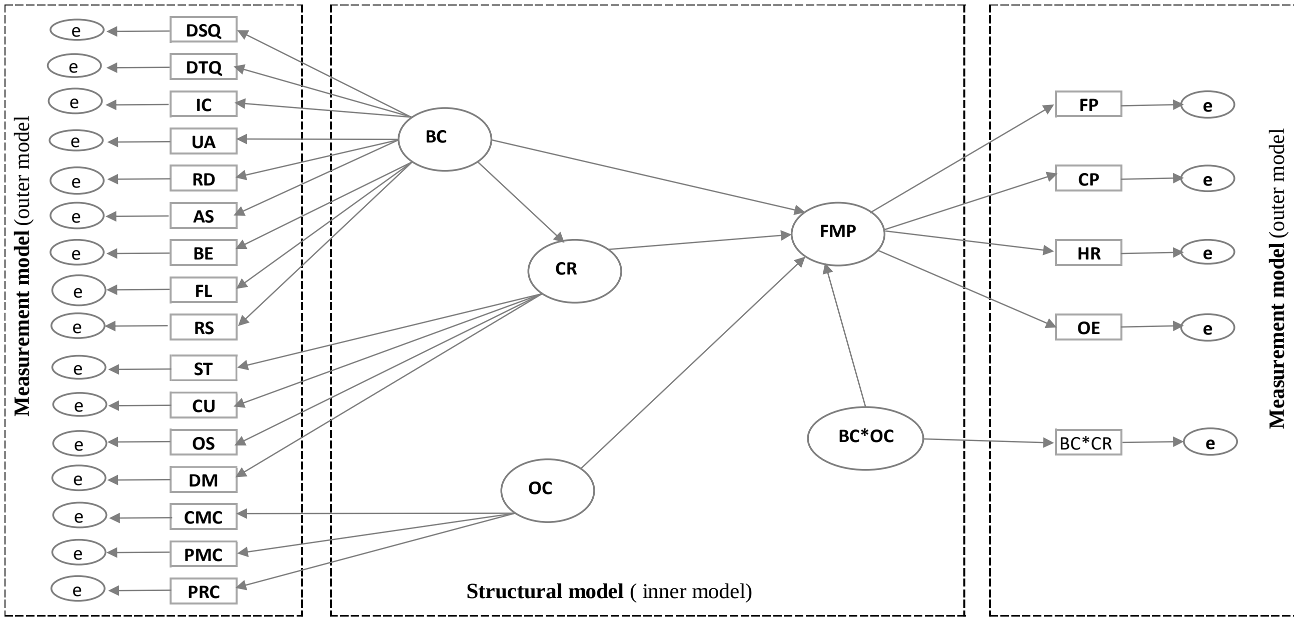

Figure 3. 4 The study's Measurement and structural model

Source: Current Researcher (2019)

Three structural sub - models that is; BI capability sub-model, Organizational capability moderating effect sub model and complimentary resources mediating effect sub-model was put in place and separately analysed to affirm the impact of each on performance. The overall model was then evaluated, perfected, and fitted to arrive at a conclusion based on the findings.

3.4.11 Outer Model (Reflective Measurement Model) Assessment

By evaluating the outer model, the researcher is confident of accurately measuring and representing the constructs that form the foundation for assessing the interactions between latent constructs. The outer model (measurement model) specifies the relationships between indicators and latent constructs. To assess the reflective outer model, Hair et al. (2014) assets that reliability and validity should be verified. Reliability is evaluated by estimating construct internal reliability while validity is measured using discriminant and convergent validity (Hair, Ringle & Sarstedt, 2011).

3.4.11.1 Reliability Tests for outer model

Reliability is a measure of how consistent results a research tool produces after repeated trials (Bryman, 2012). In quantitative research, reliability relates to consistency, stability and repeatability of outcomes. Hence, if coherent outcomes were achieved in identical situations but in distinct conditions, the findings are deemed reliable. In reflective measuring models, individual indicator reliability and reliability to internal consistency is evaluated (Hair et al. (2017).

3.4.11.2 Indicator reliability

The indicator's reliability describes how consistent set of variables, or a variable is, with what it is attempting to assess (Urbach & Ahlemann, 2010). For reflective indicators, it is evaluated by checking the outer loadings. According to Chin (1998), indicators loading should be at least 0.60 and ideally 0.70 or higher, implying that each measure represents 50% or more of the variance underlying the latent variable. Nevertheless, in social science studies, Hulland (1999) observed that researchers often obtain weaker outer loadings (< 0.70), particularly when newly developed scales are used. For exploratory studies, the author recommends a loading of 0.4 or higher. Consequently, any loads below 0.6 were dropped to improve the reliability of the indicators (Hair et al., 2014). Data is standardized in SmartPLS so that the loading of indicators varies from 0 to 1. Urbach & Ahlemann (2010) observed that the importance of the indicator loads could further be evaluated using techniques of resampling such as bootstrapping.

3.4.11.3 Internal Consistency Reliability

The traditional internal consistency criterion is Cronbach's alpha, which provides a reliability estimate based on the observed indicator variables inter-correlations. However, Hair et al. (2017) recommended the use of composite reliability because the alpha of Cronbach is sensitive to the number of items in the scale and tends to underestimate the reliability of internal consistency. In exploratory research, the authors specified that composite reliability values between 0.60 to 0.70 are acceptable. Values above 0.95 are not suitable because they imply that all indicators are measuring the same phenomenon and are thus not inclined to be a valid construct measure. These values emerge when the same question is partially reworded, utilizing semantically redundant items. Values below 0.6

imply no internal consistency reliability. Consequently, indicator with a loading value below 0.6 were dropped in order to improve composite reliability (Hair et al., 2017).

3.4.11.4 Validity Tests for outer model

The matter of validity is whether an indicator (or set of indicators) developed to evaluate a concept measure that concept (Bryman, 2012). Straub (1989) argues that there three validity issues namely instrument, internal and statistical conclusion validity that need to be tackled, for quantitative research findings to be credible. The validity of the instrument is the extent to which the instrument measures what it is intended to assess. Straub (1989, p.150) states, "*researchers need to demonstrate that developed instruments are measuring what they are supposed to be measuring"*. Hence, the instrument used in this study was evaluated using content and construct validity. Construct validity is concerned with whether indicators of a valid measure function consistently (Neuman, 2014). It reveals how well the findings of using the selected measure fit the theories around which the test is intended. It is evaluated through convergent and discriminant validity Sekaran (2003) and were employed to confirm this validity in SEM (Kline, 2015).

Internal validity brings up the issue of whether the observed impacts could have been brought about by unhypothesised and/ or unmeasured variables. It is the confidence in the cause and effect relationship in a study. Internal threats to the validity of this study were attenuated by assessing all alternatives to the degree of associations between constructs (Straub, 1989). The validity of the statistical conclusion is an evaluation of the mathematical or statistical relationships between variables and the probability that this evaluation gives the right outcome of the real covariation. It addresses the inquiry: do the two variables have an association?. Essentially, two types of relationship errors occur; concluding that there is no relationship when it actually exists and concluding relationship exists, when it does not. Threats to the statistical conclusion validity were examined using the Partial Least Square SEM to evaluate the data collected (Hair et al., 2014).

3.4.11.5 Content validity

Content validity ensures that the measure contains a sufficient representation of items taping the concept. According to Sekaran (2003), the greater the extent to which the scale items represent the domain of the measured concept, the larger the content's validity. To denote this type of validity, the instrument must demonstrate that it captures the domain of items it intends to cover reasonably and comprehensively. Face validity that is widely used in research (Neuman, 2014), was applied to assess if the instrument has measured what it is expected to measure. To ensure content validity, a preliminary questionnaire was pre-tested by two BI experts for relevance and logic. Views on the questionnaire's overall content were collected from supervisors and doctoral students.

3.4.11.6 Convergent validity

Convergent validity is the extent to which observed variables of a particular construct are highly correlated. If the results achieved with two distinct tools measuring the same concept are extremely correlated, convergent validity is established Sekaran (2003). The Average Variance Extracted (AVE) of each latent variable was assessed to verify convergent validity. AVE value is computed by generating grand mean of the squared loadings of a set of indicators. If AVE values are greater than the acceptable threshold of 0.5, convergent validity is confirmed (Wong, 2013; Hair et al., 2017).

3.4.11.7 Discriminant validity

Discriminant validity is the degree to which the construct is empirically different from other constructs (Hair, Sarstedt, Hopkins & Kuppelwieser, 2014). The establishment of discriminating validity, therefore, means that a construct is distinct and captures phenomena that is not represented in the model by other constructs (Hair et al., 2017). The Fornell and Larcker (1981) criterion is one technique for evaluating the presence of discriminating validity. This technique says that the construct shares more variance with its indicators than with other construct. To test this requirement, the square root of AVE in each latent variable should be greater than the correlation values of other latent variables (Hair et al., 2014). Another less robust option proposed by Hair et al. (2014) is to observe the indicators cross loads. Under this technique, the loads of each indicator on its construct must be greater than the cross loads on other constructs for validity to be established.

However, the latest studies critically examining cross-load efficiency and the Fornell-Larcker criterion for discriminating validity evaluation observed that neither approach detects discriminating validity problems reliably (Henseler, Ringle & Sarstedt, 2015). In particular, Hair et al. (2017) noted that cross-loading approach does not demonstrate a lack of discriminating validity when two constructs are completely correlated, making this criterion ineffective for empirical research. Equally, the Fornell-Larcker criterion execute poorly, particularly if the indicator loadings of the construct under review vary slightly. Henseler et al. (2015) suggested an alternative technique to evaluate discriminant validity based on the multitrait-multimethod matrix known as the heterotrait-monotrait correlation ratio (HTMT). The authors used simulation research to show that the heterotrait-monotrait (HTMT) ratio confirms the absence of discriminating validity. Hair et al. (2017, p.140) states, "*HTMT is the mean of all correlations of indicators across constructs measuring different constructs (i.e., the heterotrait-heteromethod correlations) relative to the (geometric) mean of the average correlations of indicators measuring the same construct (i.e., the monotrait-heteromethod correlations*)". Henseler et al. (2015) pointed out for discriminatory validity to be established, HTMT value should be below 0.90. However, Garson (2016) argues that heterotrait correlations should be lower than monotrait correlations in a well-fitting model, implying the HTMT ratio should be below 1.0.

3.4.11.8 Multicollinearity under reflective models

Multicollinearity occurs where there is high correlation among the latent exogenous constructs. In ordinary least square (OLS) regression, it occurs when two or more independent variables are strongly intercorrelated. Garson (2016, p.71) stated, "*Multicollinearity in ordinary least square regression inflates standard errors, makes significance tests of independent variables unreliable, and prevents the researcher from assessing the relative importance of one independent variable compared to another".* Garson (2016) pointed out multicollinearity is not a problem in reflective measurement model because latent variables are modelled as a predictor of indicators variables. Hence, indicators are dependent variables in reflective models. Variations in the construct, in particular, are anticipated to be reflected in all of its indicators (Henseler, Ringle & Sinkovics, 2009; Hair et al. (2017).

3.4.12 Inner Model (Structural Model) Assessment

Evaluation of hypothesized relationships within the inner model starts once the reliability and validity of the outer model is verified (Hair et al., 2014). This process enables the researcher to establish or dismiss the structural model's hypothetical proposals that depicts the conceptual model. Hair et al. (2014) argued that the evaluation of the quality of the model is based on its capacity to predict endogenous constructs. In order to obtain the most accurate parameter estimates, PLS-SEM connects the model to the sample data by optimizing explained variance of the endogenous variable(s). Hence, the researcher followed the six steps in Figure 3.5 below proposed Hair et al. (2017) to assess the structural model.

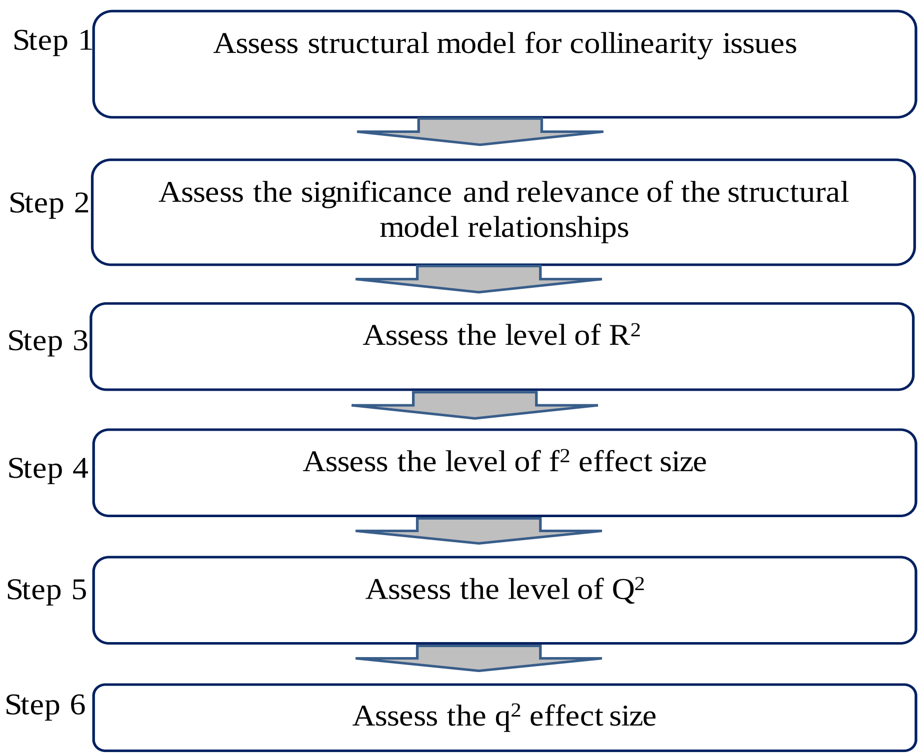

Figure 3. 5 Structural Model Assessment Procedure

Source: Hair et al. (2017).

3.4.12.1 Collinearity

This step is necessary to mitigate against bias effect among independent variables, present when collinearity exist. To evaluate collinearity, the researcher applied the same measure used in formative measurement models: variance inflation factor (VIF) proposed by Hair et al. (2017). In an ordinary least square regression assessment, this measure quantifies the prevalence of collinearity. It provides an index that attempts to measure how much the variance of an estimated regression coefficient is increased significantly due to collinearity. It is generated after running PLS algorithm and running collinearity (VIF) report under the quality criteria option. Garson (2016) argues that VIF values above 5 in the predictor constructs are deemed to be a critical level of collinearity.

3.4.12.2 Path coefficients

Estimates for the structural model relationships (the path coefficients) are extracted after running the PLS-SEM algorithm and include mean, standard deviations, t-values and p-values (Wong, 2013). The path coefficients have standard values ranging from -1 to + 1 (Hair et al., 2014). Estimated coefficients near + 1 signifies powerful positive relationships. The nearer the coefficients estimated are to 0, the weaker the relationships. Bootstrapping was also conducted to obtain standard error to enable researcher test for significance by computing of empirical t-values and p-values for all coefficients of the structural path. Commonly used critical values for two-tailed tests are 1.65 (significance level =10%), 1.96 (significance level = 5%), and 2.57 (significance level = 1%). Critical values for one-tailed tests are 1.28 (significance level = 10%), 1.65 (significance level = 5%), and 2.33 (significance level = 1%)".

The next step was to consider the relevance of the relationship to ensure the focus is on a meaningful path. Hair et al. (2014) argue that the structural model's path coefficients may be significant, but their size may be so small that merit managerial attention. When the specified path coefficient is greater than the other path, its impact on the latent endogenous variable is larger.

3.4.12.3 Coefficient of Determination (R^2 Value)

The R^2 is a measure of the predictive accuracy of the model and is computed as the squared correlation between the actual and expected values of a particular endogenous construct. The coefficient reflects the combined impacts of exogenous latent variables on the endogenous latent variable (Hair et al., (2014). Hence, the measure generates insights into the predictive power of a model (Benitez, Henseler, Castillo& Schuberth, 2019). The R^2 value spans from 0 to 1, with 1 reflecting greater predictive accuracy. As a general thumb rule, R^2 values of 0.75, 0.50, or 0.25 may be defined as significant, moderate, or weak respectively.

However, Hair et al. (2017) stated that it is not a good strategy to select a model based exclusively on the R^2 value. For example, adding a non-significant construct to demonstrate the structural model's endogenous latent variable always raises its R^2 value. The authors recommended the adjusted determination coefficient (R^2) be used to prevent bias towards complicated models. This criterion is adjusted to reflect the number of exogenous constructs with reference to the sample size. This measure is generated after running PLS algorithm, then R Square report under quality criteria option in SmartPls.

3.4.12.4 Effect size (f^2)

The Cohen's f^2 measure relates to a change in R^2 for a particular path when specified exogenous construct is omitted from the model, in order to investigate whether the omitted construct has a significant effect on the independent constructs. The measure evaluates how strongly an exogenous construct helps to explain identified endogenous construct in relation to R^2. The effect size is computed as $f^2 = (R^2_{Included} - R^2_{Excluded})/R^2_{Included}$ (Hair et al., 2017).

The guidelines set by Hair et al. (2014) were followed in computing this measure. Hence, the researcher estimated two PLS path models in computing the effect size. The full model as designated by the hypotheses was the first path model, yielding the full model's R^2. The second model, identified exogenous construct was removed from the model, resulting in the decreased model's R^2. It is generated after running PLS algorithm, then f square report under quality criteria option in SmartPls. The effect size of the omitted construct for a specific endogenous construct can be determined on the basis of the f^2 value in such a way that 0.02, 0.15 and 0.35 represent small, medium and large impacts respectively. Effect size values below 0.02 show that no impact exists (Hair et al., 2017).

3.4.12.5 Cross-validated redundancy (Q^2).

Stone-Geisser's Q^2 is a measure for evaluating the predictive relevance of the inner model by carrying out a blindfolding procedure. Data not used in the model estimation is predicted accurately when PLS path model shows predictive relevance. The measure is based on a sample reuse method that omits a portion of the data matrix, estimates the parameters of the model and predicts the omitted portion using estimates (Hair et al., (2014). Blindfolding is a sample reuse method that systematically removes data points and gives an estimate of the initial values. The operation demands omission distance "D" to be specified. Hair et al. (2017) recommends an omission distance between 5 and 7. An omission distance of five (D=5) means that in a single blindfolding round, each fifth data point of indicators of a latent variable will be eliminated.

The operation begins with the first data point during the initial blindfolding round and omits every D^{th} data point of a latent variable's indicators. The PLS path model is approximated using the residual data points. When running SmartPls, the omitted data points are treated as missing values using mean value replacement or pairwise deletion option. The outcomes of PLS-SEM are then used to gauge the omitted data points (Hair et al., 2014). Blindfolding process is repeated until each data point of the indicators of a latent variable is removed and then selected. The lesser the gap between the predicted values and the original values, the better the Q^2 and the predictive accuracy of the model. Hair et al. (2014, P.178) states "*In the structural model, Q^2 values larger than zero for a certain reflective endogenous latent variable indicate the path model's predictive relevance for this particular construct.*" The zero and below Q^2 values show a lack of predictive relevance (Urbach & Ahlemann, 2010) and hence independent variable cannot expain the dependent variable.

There are two approaches for computing Q^2; cross-validated redundancy and cross-validated communality (Hair et al., 2017). Cross-validated redundancy approach is based on the path model estimates of the measurement model (target endogenous construct) and structural model (scores of the antecedent constructs) to forecast data points that are left out. The cross-validated communality utilizes the estimated construct results only (without structural model data) for the target endogenous construct to predict omitted data points.

This study adopted cross-validated redundancy approach in reference to the recommendation by Hair et al. (2017), because it involves the structural model (the path model's main component) to predict discarded data points.

3.4.12.6 The effect size q^2

This measure makes it possible to evaluate the contribution of an exogenous construct to an endogenous latent variable's Q^2 value. It is defined as follows: $\mathbf{q^2} = [Q^2 \text{ (included)} - Q^2 \text{ (excluded)}] / 1 - Q^2 \text{ (included)}$. It is calculated manually because it is not provided by the SmartPLS software. Hair et al. (2017, p.216) states, "*as a relative measure of predictive relevance, q2 values of 0.02, 0.15, and 0.35, respectively, indicate that an exogenous construct has a small, medium, or large predictive relevance for a certain endogenous construct".*

3.4.12.7 Goodness-of-fit Index

Although GoF's use has lately become increasingly widespread as an index to assess the general model fit in PLS path models, its usefulness has been challenged by Henseler and Sarstedt (2013) empirically and conceptually. Their study demonstrates that the GoF for PLS-SEM does not constitute a criterion of goodness-of-fit because it cannot separate valid from invalid models. Further more, the authors argued that the measure is unfit for identifying unspecified models. Consistent with aforementioned argument, Hair et al. (2017, p.204) stated;

"*it is an open question whether fit measures as described above adds any value to PLS-SEM analyses in general……. PLS-SEM focuses on prediction rather than on explanatory modeling and therefore, requires a different type of validation. In fact, their use can even be harmful as researchers may be tempted to sacrifice predictive power to achieve better fit. Therefore, we advise against the routine use of such statistics in the context of PLS-SEM."*

Hence, covariance-based goodness-of-fit measures cannot be fully transferred to PLS-SEM. The fit measures focus on the discrepancy between the observed or approximated values of the dependent variables and the predicted values of the model in question. Garson (2016) observed that GoF cannot be processed by SmartPLS, consequently, it has to be computed manually. It is recommended that researchers do not use this metric (Hair et al., (2014). This measure was not used in this study.

3.4.13 Moderation Analysis in Structural Equation Modelling

Moderation defines a case in which the connection between two constructs is not continuous but depends on a third variable's values. The moderator shifts the intensity or even direction of a connection in the model between two constructs (Hair Jr, Hult, Ringle & Sarstedt, 2017; Hair et al., 2017; Becker, Ringle & Sarstedt, 2018). The prevalence of numerous techniques to estimate moderating effect in SEM has significantly led to the absence of agreement on the correct approach (Little, Bovaird & Widaman, 2006). Four main approaches have been identified in literature for testing moderating effect, that is a product indicator approach, a 2-stage approach, a hybrid approach, and an orthogonalizing approach (Henseler & Chin, 2010).

The product indicator approach encompasses multiplication of each indicator of the moderator variable with each indicator of the exogenous latent variable to create latent interaction term (Hair et al., 2014). Therefore, if there are X indicators for the exogenous latent variable and the moderator has Y indicators, the latent interaction term will have X.Y indicators. Chin et al. (2003) originally proposed the concept of the two-stage approach. It extends the product indicator approach. It consists of two stages (Henseler & Chin, 2010). In stage one, the primary effects model is assessed without the interaction term. The second stage involves multiplication of the latent variable results of the Stage 1 and moderator variable to generate a single-item measure used to evaluate the interaction term.

This study adopts orthogonalizing method to test moderating the role of organisational capability between BI and firm performance. This method is preferred because it does not necessitate imposing constraints on projected parameters and can be executed by employing any SEM software (Hair et al., 2014). Henseler and Chin (2010) recommended this approach should be used when dealing with a small sample and the construct has few indicators. Hair et al. (2017) further underscored the preference of this approach because it generates high prediction accurancy. The orthogonalizing method, developed by little et al. (2006), is an improvement to product indicator approach designed to address the issue of standardization that results in inflated standard error (Hair et al., 2017; Becker et al., 2018). This approach comprises of two phases when testing for moderation (Henseler & Chin, 2010). The first phase includes the generation of interaction term indicators by obtaining the product of first-order variable indicators. Then each product indicator is regressed against first-order indicators that each product term has generated. Residuals of regression are kept as interaction latent variable indicators that are orthogonal to the latent constructs of the first order. In phase two, in the latent interaction model, the residuals are then used as indicators of the product construct.

3.4.14 The Mediation Analysis in Structural Equation Modelling

Pardo and Roman (2013) defined mediation as a causal chain in which it is presumed that the effect of one or more independent variables is conveyed to one or more dependent variables through third variables. According to Hair et al. (2017), the mediator variable's task is then to disclose the real connection between dependent and an independent construct. To test mediation in SEM, literature highlights three main approaches; Baron and Kenny (1986) mediation analysis, the bootstrap method and Sober test (Hadi, Abdullah & Sentosa, 2016). Mediation analysis under Baron and Kenny approach, consists of four main steps. First, the investigator must identify that the dependent and independent variables have statistical significance. Second, the researcher must demonstrate that the independent variable and the mediating variable have statistical significance; for example, between BI capability and complementary resources. Next, the researcher must then show a statistical significance between the variable mediating and the dependent variable. For instance, between complementary resources and firm performance. Finally, after including mediating variable, the researcher then evaluates the impact. According to Hadi et al. (2016), if the mediator's incorporation nullifies the direct relationship, there is complete mediation; otherwise, mediation will be partial or absent.

The Sobel test is another approach used to assess the mediator's relevance by identifying the product of coefficients item (Hadi et al., 2016). The Sobel test is essentially a precise test that provides a technique for determining whether the reduction in the impact of the independent variable, after including the mediator in the model. Hence, the researcher is able to determine whether the mediated impact is statistically notable. Sobel’s test explores the “c” region (refer to Figure 3.6 below). If the “c” region is bigger than the “d” region, it is significant as per Sobel’s test and hence, indication of mediation. However, this approach has been criticized on the ground that it relies heavily on distributional assumptions, although the distribution of indirect effects sometimes is asymmetric according to Hair et al. (2014). This asymmetry impacts Sobel's test's applicability when working with small sample sizes. Hadi et al. (2016) observed that the distribution of the indirect effect is normal only at large sample sizes.

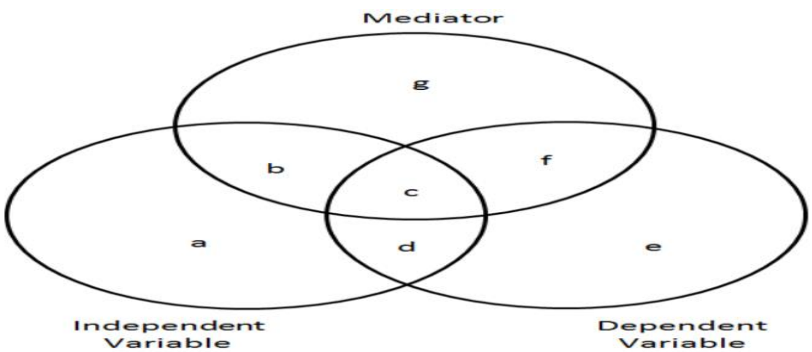

Figure 3.6 Venn diagram approach

Source: Hadi et al., 2016)

In bootstrapping, a large amount of subsamples (bootstrap samples) are generated with replacement from the initial data set. Replacement means that each instance of subsample taken is returned to the sampling population to be part of the next draw. According to Hair et al (2014), this operation is repeated until a large amount of randomly derived subsamples are produced to estimate the path model. The bootstrap method is a resampling test that is not parametric (Hadi et al., 2016). Hair et al. (2017) observed that this technique produces greater statistical power than sobel test. The primary characteristic of this test is that it does not depend on normality assumption (Hair et al., 2014) and it is therefore, suitable for smaller sample sizes (Pardo & Roman, 2013) hence, adopted in this study.

Complex model reporting is a challenge, and therefore researchers often draw conclusions concerning mediation analysis based on specified steps rather than a single process (Hadi et al., 2016; Wong, 2016; Nu'man et al., 2020). Hair et al. (2014) descried significance of mediation analysis in their book “*A Primer on Partial Least Squares Structural Equation*

Modelling (PLS-SEM)" and further validated that mediation analysis is a step-by-step activity. Hence, bootstrapping was broadly conducted in two steps. Firstly, without mediation, and hence, testing direct link between BI capability and performance. Secondly, with the presence of mediation (Hadi et al., 2016; Hair et al., 2014). If indirect path between BI, complementary resources and Firm performance is not significant, there is no mediation (Preacher & Hayes, 2008). If significant, variance accounted for (VAF) will be computed. VAF is computed by indirect effect over total effect (direct effect plus indirect effect). VAF value of greater than 80% means full mediation, between 20% and 80% is partial mediation and less than 20%, means no mediation (Hair et al., 2014).

To further simplify the mediation process, above steps were amplified into four steps (Schultheis, 2016) as shown in figure 4.15. Step one focused on assessing the significance and nature of relationship between an independent and dependent variable. Step two then tested the relationship between independent and mediating variable. Step three tested the effect of the mediating and the dependent variable. Step four finally evaluated the influence of the mediating variable on the relationship between independent and dependent variable.

Table 3.3 below summarizes measures used, the criteria, what to look for/ where various reports are located in SmartPLS.

Table 3. 3 Measures, Criteria and location of reports in SmartPLS

Measure	**What to look for in SmartPLS**	**Where is it in the report**	**Criterion**	**Description**	**Literature**
Indicator reliability	"Outer loadings " numbers	PLS, calculate, Algorithm, Final Results, outer Loadings.	0.70 or higher is preferred.	Loadings constitute the indicator's absolute contribution to its latent variable definition.	Urbach and Ahlemann, (2010), Chin (1998), Hair et al. (2014), Wong et al. (2013).
Internal consistency reliability	"Reliability" numbers	PLS, calculate, algorithm, quality criteria, construct liability,	Composite reliability should be 0.7 or higher.	Is a measure of how well the items on a test measure the same construct.	Hair et al. (2017), Urbach and Ahlemann

		composite reliability			(2010), Garson (2016).
Convergent validity	“AVE” numbers	PLS, calculate, algorithm, quality criteria, construct liability and validity, AVE	Average variance Extracted (AVE) should be > 0.5	The extent to which observed variables of a particular construct are highly correlated	Sekaran (2003, p.206), Wong (2013), Hair et al. (2017)
Discriminant validity	Cross-loadings	PLS, calculate, algorithm, quality criteria, discriminant validity, cross loadings	loadings of each indicator should > cross loadings on other constructs	degree to which the construct is empirically different from other constructs	Urbach and Ahlemann (2010),Wong (2013).
Discriminant validity	Fornell-Larcker	PLS, calculate, Algorithm, quality criteria, discriminant validity, Fornell larcker.	“square root” of AVE of each Latent variable (LV) should be > correlations among the LV	Demands an LV to share more variance with its allocated indicators than with any other LV	Fornell and Larcker (1981), Hair et al. (2017).
Discriminant validity	Heterotrait-Menotrait Ration (HTMT)	PLS, calculate, Bootstrapping, quality criteria, HTMT.	HTMT < 1	It measures average correlation among indicators across constructs divided by the average correlation among indicators within the same construct	Henseler et al.(2015), Hair et al. (2017)
Collinearity	variance inflation factor (VIF)	PLS, calculate, Algorithm, quality criteria, collinearity statistics (VIF), inner VIF values.	VIF >5	Measures how much the variance of an estimated regression coefficient is increased due to collinearity.	Hair et al. (2017).

Path coefficients	Mean, STDEV and t-values	PLS, calculate, Bootstrapping, path coefficients.	Critical t-values for a two-tailed test are 1.65 (sig. level = 10 %), 1.96 (sig. level = 5%), and 2.58 (sig. level = 1%.	They are path weights linking statistical variables in SEM modeling approach.	Wong (2013), Hair et al. (2014), Hair et al. (2017)
Coefficient of Determination (R^2 Value)	R^2 value	PLS, calculate, algorithm, quality criteria, R Square report	$R^2 > 0.100$ 0.75 Significant 0.5 moderate 0.25 Weak	Measure of the predictive accuracy of the model	Hair et al. (2014). Urbach and Ahlemann (2010)
Effect size (f^2)	f^2 value	PLS, calculate, algorithm, quality criteria, f Square report	Values of 0.02, 0.15 and 0.35 represent small, medium and large impacts.	Measures if an independent LV has a substantial impact on a dependent LV	Hair et al. (2014). Urbach & Ahlemann (2010)
Cross-validated redundancy (Q^2).	Q^2value	PLS, calculate, Blindfolding, Final result, construct crossvalidated redundancy report	Threshold value is $Q^2 > 0$	A measure for evaluating the predictive relevance of the inner model	Hair et al. (2017, p.213), Garson (2016). Urbach & Ahlemann (2010).
Effect Size q^2	Computed q^2 value	Not available in SmartPLS. It manually computed as shown under section 3.4.12.6	Values of 0.02, 0.15 and 0.35 represent small, medium and large predictive relevance.	The measure indicates if exogenous construct has a small, medium, or large predictive relevance.	Hair et al. (2017)

Source: Adapted from Urbach and Ahlemann (2010) and Wong (2013).

3.5 Qualitative Strand of the study

3.5.1 Justification for Using Qualitative Approach

The deliberate use of the qualitative method for this study was guided by the underlying advantages of the qualitative research elucidated by Basias and Pollalis (2018). First, this approach permits the nature and complexity of the phenomenon under consideration to be fully grasped. Second, it advances research in fresh fields, particularly when examining a phenomenon in its natural environment. This strategy also supports in-depth research on the subject matter (Yu & Khazanchi, 2017). Qualitative research aims at gaining knowledge of the nature and shape of events, unpacking meanings, developing explanations or generating ideas, concepts and theories (Ritchie et al., 2014). The current study entails to great extent user's perception on BI impact hence, opportunity to listen to participants is paramount. This tool is appropriate for this study because BI is a relatively new phenomenon in IS research and therefore, comments from respondents is expected to shed more light on the subject matter.

3.5.2 Sampling

Ritchie et al. (2014) recommended nonprobability method to deliberately select samples reflecting particular features of interest. The authors identified three sampling approaches used in a qualitative inquiry; Purposive or criteria-based sampling; opportunistic sampling; convenience sampling and theoretical sampling. For the research using deliberate or purposive sampling, instances are "handpicked" (Denscombe, 2007). It is used in situations where the investigator already knows about the individuals or events and deliberately chooses them as cases where valuable data is generated. Denscombe (2007) observed that it is the most common sampling technique used for case selection. Hence, purposive sampling was adopted for this study to ensure participants knowledge and experience on the subject are selected.

Dworkin (2012) suggested a sample size of not more than fifty but not less than five participants for an in-depth study. According to Dworkin, the sample size used during qualitative methods is often smaller than that used in quantitative studies. This is because qualitative methods of studies often involve gaining a thorough knowledge of a phenomenon hence, the need to ensure data is properly analysed. Echoing the need for smaller sample size, Richie et al. (2014, p.84) stated, "*Qualitative research is highly intensive in terms of the research resources it requires. It would therefore, simply be unmanageable to conduct and analyse hundreds of interviews, observations or groups unless the researcher intends to spend several years doing so*." In a qualitative study carried out by Kamau (2017), data was collected from nine informants. Furthermore, in a study by Yohannis (2019), fourteen informants were targeted. Twelve informants were targeted, one from each of the ten sectors represented on the NSE. However, for the commercial and banking sector, the number was increased to two due to the large numbers of firms under these categories. Nevertheless, it was impossible to get an appointment in investment, construction and automobile sector in spite of several attempts, hence, excluded. Therefore, eight key informants with knowledge and experience in BI were selected for this study.

3.5.3 Qualitative Data Collection

In a qualitative study, there are two primary techniques to data collection; in-depth interviews and focused groups (Richie et al. (2014). In-depth interview is a research technique that focuses on rigorous individual interviews with few participants to explore their views on a specific concept. Main forms of qualitative interviews identified by Saunders et al. (2009) include structured interviews, semi structured interviews and unstructured interviews. Structured interviews use questionnaires based on a predetermined set of questions. Unstructured interviews are casual and do not follow a set of questions defined in advance. Semi-structured interview was adopted in this study. This approach enabled the researcher to control the discussion based on predetermined questions (Llave et al., 2018) and at the same permitting some level of informality to explore and capture additional pertinent issues relating to the study.

The interview process consisted of three phases; preparation, introduction and asking questions. Preparation phase involved gathering initial data about the interviewee and drawing up topic guide. Richie et al. (2014) pointed out topic a guide is strongly advised in qualitative research and considerate investment in their layout is paramount because it provides documentation of topics to cover hence, serves as a research agenda. It helps to guarantee that important issues are dealt with in a systematic and uniform manner, while enabling flexibility to follow other details that are crucial to each respondent. Richie et al. (2014, p.115) states, "*Displaying topic guides in study reports is an important element of documenting the research approach and making it transparent*". Topic guide (Appendix II) used in this study had three sections. The first section covered the research objectives. The second section covered background information such as position of the respondent. The final section targeted in depth response on major variables.

Face to face interview approach was adopted, with researcher taking notes on critical issues mentioned during the session and at the same time recording the conversation (Llave et al., 2018). By recording the interview session, the researcher was able to concentrate in greater depth and listen closely to what has been said and at the same time paying attention to expressions and other nonverbal signs. General principles of interview highlighted by Richie et al. (2014) were followed during the interview session. First, was research introduction covering clear restatement of the research's nature and purpose, reaffirming confidentiality, and seeking approval to record the interview and assurance of confidentiality. Second, the data relating to participant was collected, for example, years of experience. Variables used in the study were identified and defined. The discussion flowed chronologically from the top with few instances of forward and backward referencing. Notes were examined immediately following the interviews to determine the core elements. Generally, the process of data collection was successful save for few instances of disruption during the interview process. The interviews were largely held in respondent's offices.

3.5.4 Researcher's role during the interview

The researcher demonstrated the task of an active listener during the interview. The researcher listens intimately to the interviewee without interrupting or arguing over their views on the questions asked. The information about the study, objectives and the rights of the respondent was highlighted at the start of the interview. Consent to record was requested, voluntary participation and obligation not to respond to questions was expressly mentioned. Participants were also notified of their prerogative to withdraw from the process at any time, including withdrawing data provided. They were also given a chance ask questions before and after the interview. The interview was premised on a conversation approach.

3.5.5 Reliability Tests

Reliability in qualitative approach generally relates to the replicability of research results and whether they would or would not be replicated if another study was undertaken using the same or comparable techniques (Ritchie et al., 2014). There have been numerous questions about the extent to which replication can happen in qualitative research. For example, Ali and Yusof (2011) strongly argued that the issue of reliability is linked to measurement instruments, hence, it is inapplicable in qualitative research. Cohen et el. (2007) noted the term reliability in qualitative research is contested, hence many researchers prefer to substitute with terms such a ‘credibility’, ‘neutrality’, ‘confirmability’, ‘dependability’, ‘consistency’, ‘applicability’, ‘trustworthiness’, ‘transferability’, and ‘dependability’. Ritchie et al. (2014) contends that the challenge is for researchers to demonstrate if these qualities exist and how they can be measured.

In spite of existing conflicting views over the quality criterion of reliability in qualitative inquiry, Morgan and Drury (2003) detailed how qualitative research can attain an appropriate level of research reliability adopted in this study. Reliability was achieved by ensuring data generation methods are fully defined and recorded to enable the reader to exercise joint accountability with the researcher in assessing the proof on which the findings are based. Structured questions were asked to ensure reliable feedback from respondents. Efforts to shun leading questions and other possible bias during interview session, was given special focus. The researcher used a constant coding scheme to enhance reliability throughout the phase of data analysis (Cohen et el., 2007).

3.5.6 Validity Tests

Validity in qualitative research mainly refers to the issues relating to representation, understanding and interpretation. The primary validity question is whether the research correctly reflects the phenomena being investigated as perceived by the population studied (Ritchie et al., 2014). However, designing validity benchmarks in qualitative research is complicated to interviewer bias and subjectivity deeply embedded in the analytical process. (Whittemore, Chase & Mandle, 2001; Ritchie et al., 2014). The bias and subjectivity of the researcher embedded in the data analysis method present a significant risk to the validity of qualitative research. Ritchie et al. (2014) pointed out that this challenge is aggravated by underlying doubt in the minds of many qualitative researchers that there are hardly effective means of confirming accuracy or truth in social research.

To minimise validity threats, the study adopted techniques proposed by Whittemore et al. (2001). First, is the design consideration achieved by ensuring sampling adequacy and employing triangulation. Second, is data generating technique by providing verbatim transcription, demonstrating saturation, cross-checking data from different interviews on the same phenomenon and articulating data collection decisions. Third, is the analytic technique by stating data analysis decisions, expert checking the work, cross-referencing to documented records and exploring rival explanations. Fourth, is the presentation technique by availing an audit trail and providing evidence that support interpretation.

3.5.7 Pilot Testing

A pilot testing on the qualitative strand was carried out to identify questions that make participants uneasy and any tendency for participants to lose interest at certain points is detected (Bryman, 2012). Saunders et al. (2009, p.394) postulate that "*the purpose of the pilot test is to refine the questionnaire so that respondents will have no problems in answering the questions and there will be no problems in recording the data. In addition, it will enable you to obtain some assessment of the questions' validity and the likely reliability of the data that will be collected. Preliminary analysis using the pilot test data can be undertaken to ensure that the data collected will enable your investigative questions to be answered".* The researcher sort feedback from director of finance and chief information officer who had successfully implemented BI in their respective organisations. The two participants had over five years' experience in using the application. The pilot dealt with questions, the wording and phrasing of questions, translations and question sequence. The feedback from this process was reviewed and additional probing questions were added. For instance, definition of key concept such as business intelligence was not clear. Hence, a brief description was included in the topic guide as shown in appendix II.

3.5.8 Qualitative Data Analysis

Thematic and content analyses are the main techniques used to analyse qualitative data. However, thematic analysis is seen as a foundation method for qualitative analysis. It is a method for identifying, assessing and documenting themes in the data collected. It was used in this study because of its flexible and can generate deeper and richer insights from data (Braun & Clarke, 2006). It also has the ability to summarise sophisticated qualitative data by discovering hidden themes. The authors identified two approaches to thematic analysis; inductive and theoretical analysis. Inductive analysis is a process of coding the data without attempting to reference into a pre-existing code frame. Theoretical analysis tends to be driven by the theoretical interest of researchers in the field. This approach was adopted in this study since data analysis was carried in reference to specific research questions.

Braun and Clarke (2006) provide a step-by-step roadmap for undertaking thematic analysis. The roadmap was adopted in this study and include data familiarization, coding, searching for themes, reviewing and developing analytical codes. Before starting the analysis process, recorded conversations were transcribed into a written form. At this stage, errors in transcribed data were corrected by reading and listening to the recorded conversion at the same time. The researcher familiarised himself with text by reading and re-reading the data while noting down background information such as experience, education level and gender. Coding can be performed by line or in blocks, such as a phrase or paragraph. It can be performed manually or using software. Gibbs (2007) describes coding is an activity indexing qualitative data to detect and isolate various themes and their association. The researcher coded the data in this research using Atlas.ti version 8. Hence, all the interviews were uploaded to Atlas.ti, thereafter, commenced a strict coding process for each response. A relevant code was assigned to applicable data segment (quotation). The length of quotations assigned to a code differed. Sometimes a quotation consisted of one response, or several sequential responses on the same theme. Atlas.ti offers multiple methods to use codes for further evaluation after coding the appropriate text and quotations in uploaded documents (Paulus et al., 2017). For instance, you can search and compare data segments depending on the codes you have allocated. Using Atlas.ti for coding inspires interactive approach to data analysis that would have been hard to achieve via note cards, word processing or spreadsheets (Lewis, 2016). Finally, output from Atlas.ti was then extract into excel for quantizing. Figure 3.7 below indicate steps followed in analyzing the data.

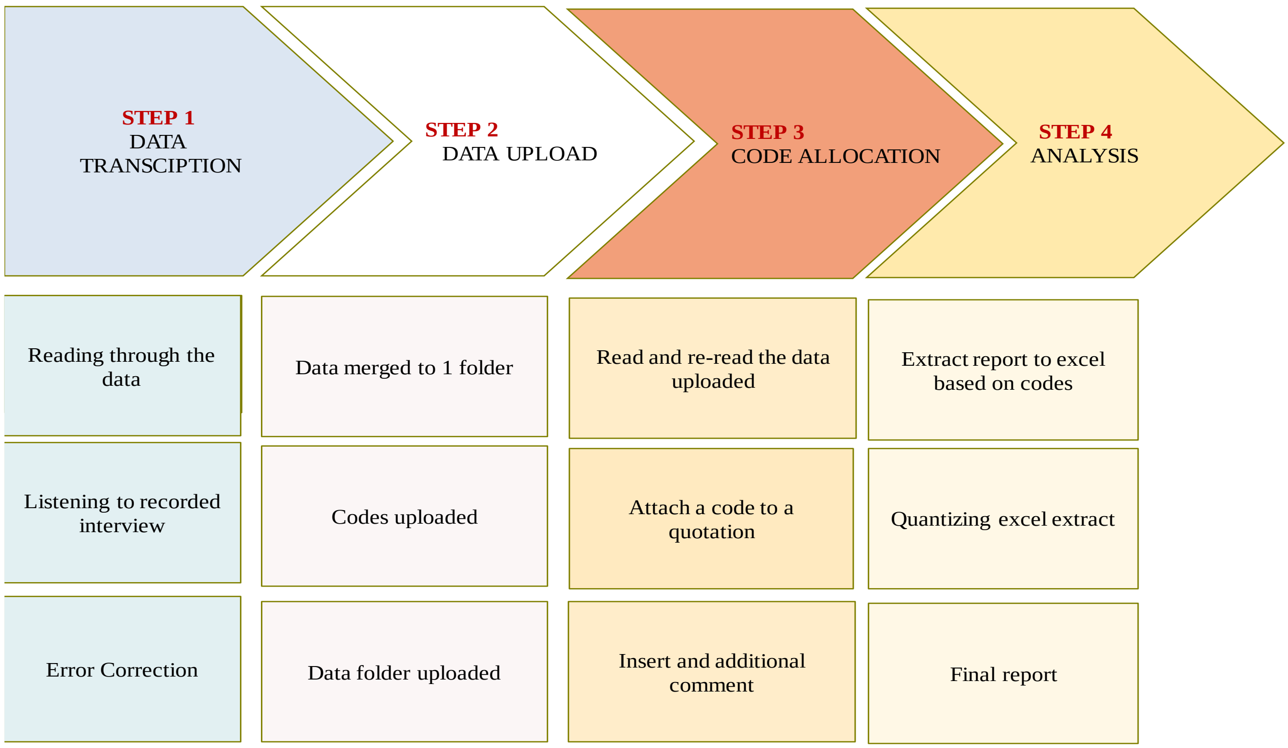

Figure 3. 7 Qualitative data analysis process

Source: Adopted from Braun and Clarke (2006)

The data codes and categories used to assess the data in this study were gleaned from current theories and a predefined conceptual framework, as asserted in table 3.4 below.

Table 3. 4 Coding of Qualitative data

Theme	Sub-theme	Codes
	Data source quality	Internal/external source
	Data type quality	Structured /unstructured data
	User access	Multiple users/Access levels
	Data reliability	Dependable

Business Intelligence Capability	Interaction	Connectivity
	Analytical skills	Training
	BI experience	Duration of BI use
	Flexibility	Scalability/modularity
	Risk management	Performance monitoring
Organisational Capability	Customer management	Complains/Service level agreements
	Process management	Key performance indicators
	Performance	Variance Analysis/performance reviews
Complementary Resources	Decision making process	Customised reports
	Culture	Resistance to change /cooperation/ management style
	Structure	Centralised/decentralised
	Organisation strategy	Business plan/forecasting/business acquisitions
Firm Performance	Sales growth	Revenue increase
	Customer performance	Increase in customers base
	HR performance	Morale/Staff turnover
	Organisation effectiveness	Efficiency/profitability

3.5.9 Ethical Consideration

Ethical consideration relates to concerns on how we formulate and explain study topic, structure research, gain access, gather data, process and store information, dissect data and write study results morally and responsibly (Saunders et al., 2009). Within business management studies, the authors identified two prominent philosophical perspectives: teleology and deontology. The teleological point of perspective claims that the purpose of your research justifies the approach even if it means acting unethically. This study adopted deontological views, which argues that the aims of the study can never justify the use of unethical process.

In this study, the researcher took into consideration ethical standards highlighted by Eybers (2015). Hence, the researcher ensured data is correctly documented to reflect the actual state of the findings. Furthermore, required concert was sort and granted from all respondents before commencing the interview. Respondent rights were explicitly expressed. For instance, voluntary involvement in the research and the right to exit at any moment from the research. Measures were taken to guarantee the privacy and dignity of respondents when using voice recordings. Respondents were guaranteed that the results will be used solely for scholarly purposes. All possible ethical concerns were appropriately addressed.

3.6 Chapter Summary

This chapter presented an overview of the research strategies used to understand BI's impact on performance, taking into account the moderating effect of organizational factors and the mediating effect of complementary resources. The chapter started by identifying philosophical paradigms in IS research that include positivism, interpretivism and pragmatism. The study settled on pragmatism perspective because it attempts to find a common position where both positivism and interpretivism are accommodated. Hence, the study was guided by mixed method approach that involves combining elements of qualitative and quantitative approaches.

This study used a cross-sectional mixed methods design. Cross-sectional survey involves collecting data at a particular time point across different members of a population. Triangulation design was adopted to obtain different but complementary data to best understand the impact of BI on performance. The target population of the study was firms listed at the Nairobi Securities Exchange. The researcher applied the Structural Equation Modeling (SEM) analytical technique to analyse quantitative data. Partial Least Squares SEM (PLS-SEM) was chosen since it can conveniently embrace single-item metrics and also obtain solutions from other more complicated models. SmartPLS version 3.0 was used. Thematic approach was used in analysing qualitative data because it has the ability to summarise intricated qualitative data by uncovering concealed themes. Data that had been collected through interviews was coded and analysed using Atlas.ti version 8.

CHAPTER FOUR

QUANTITATIVE DATA ANALYSIS RESULTS

4.1 Introduction

The results of quantitative data analysis are discussed in this section. A Pilot survey was undertaken to evaluate the initial items of the study to ascertain whether any measurement change was required before the main research commenced. The main research begun after pre-test process. A revised questionnaire was used to gather data on a 5-point Likert scale. The chapter addresses the study results as follows: survey response frequency, respondents' demographic characteristics and then some descriptive company profile metrics. The discussion on data preparation, measurement and structural model is included in this section. Validity and reliability test for measurement model is also highlighted. The structural model is evaluated in order to test the hypotheses. Interpretation of the study findings are discussed in the last section. The software tool (SmartPLS 3.2.1) was employed to perform PLS-SEM analysis.

4.2 Response Rate

The target population of the study was firms listed at the Nairobi Securities Exchange (NSE) totalling to 64 as at 31st December 2018. However, in September 2019, Mumias Sugar was placed under receivership and all staff made redundant, hence, was excluded. All other listed companies (63) were contacted to participate in completing the questionnaires.

A total of 57 respondents returned their filled responses out of 63 targeted firms, translating to 90% response rate. There was enough response rate for further data analysis. Baruch and Holtom (2008) asserted that for a cross-sectional survey, a response rate of 35.7% is sufficient. Previous studies have yielded lower response rate, for example, Wambugu (2018) 43% and Busienei (2013) 69.4 %. This response rate was aided by a research clearance permit from the National Commission for Science, Technology and Innovation, a personal letter of introduction and a letter from Nairobi University.

4.3 Data Preparation and Coding

The data gathered was subjected to a thorough review of completeness, consistency and accuracy. The main issues addressed include omitted data, outliers, and unusual response patterns/ inconsistent responses (Hair et al., 2017). Out of 57 collected questionnaires, 2 were found to be unusable and thus excluded. In one questionnaire, few responses were found to have over 30% missing data due to possible error of omission or intentional failure by the respondent to answer certain questions. When the quantity of omitted data on a questionnaire is above 15 percent, Hair et al. (2017), advises that the observation should be deleted from the data file. Hence, it was excluded. The other questionnaire was rejected because it was a duplicate from the same company. The data for subsequent review, therefore, was based on a total of 55 questionnaires.

SmartPLS does not have an option for direct entry of data. Hence, valid questionnaires were arranged and coded using SPSS version 20. To avert data entry errors, the variable titles and labels in SPSS mirrored those in the questionnaire. The researcher manually counter checked the data file to the questionnaires because of the small data set. Few entry errors we flagged and corrected, for example, misalignment of a score and assigned weight. A preliminary analysis was carried out using SPSS. After completing data, it was saved as CSV file and exported into the SmartPLS software. Few indicators on the retained questionnaires had less than 5% missing values. The missing values were handled in SmartPLS by selecting the mean value replacement approach. Under this approach, missing values are replaced by that indicator's average of all valid values (Hair et al. (2017).

Data was also examined to identify outliers attributed to entry errors. No outlier values were identified. Data was largely collected on a 5-point Likert scale and hence, mitigating the risk of entering erroneous values. All recorded values in SPSS ranged between 1 and 5. Normality test was also carried out as part data preparation process. Although PLS-SEM is a non-parametric statistical method, suggesting that it does not require the data to be distributed normally, Hair et al. (2017) argue that data, which is too far from normal is inappropriate in the parameter assessment. The authors recommended skewness and kurtosis measures to be used to examine data distribution. As indicated in Appendix VI, parameters generated for indicators were within the acceptable rage of +1 and –1. It implies that data was normally distributed (Hair et al., 2011).

4.3.1 Demographic Analysis

In this study, demographic analysis includes a description of how respondents are distributed by job title, working experience in the current organisation, response rate in terms of the sector in which the company operates, and BI tool in use.

4.3.1.1 Response rate by work experience

The respondents were required to state how long they had been working with their current employer. More than 62 percent of the respondents have stayed for ten years and below in their present organization. It is an indication of high staff turnover. Only 11% have remained in their present organisations for more than 16 years. The responses are presented in Figure 4.1. The findings suggest that the respondents were generally well equipped to answer the research questions.

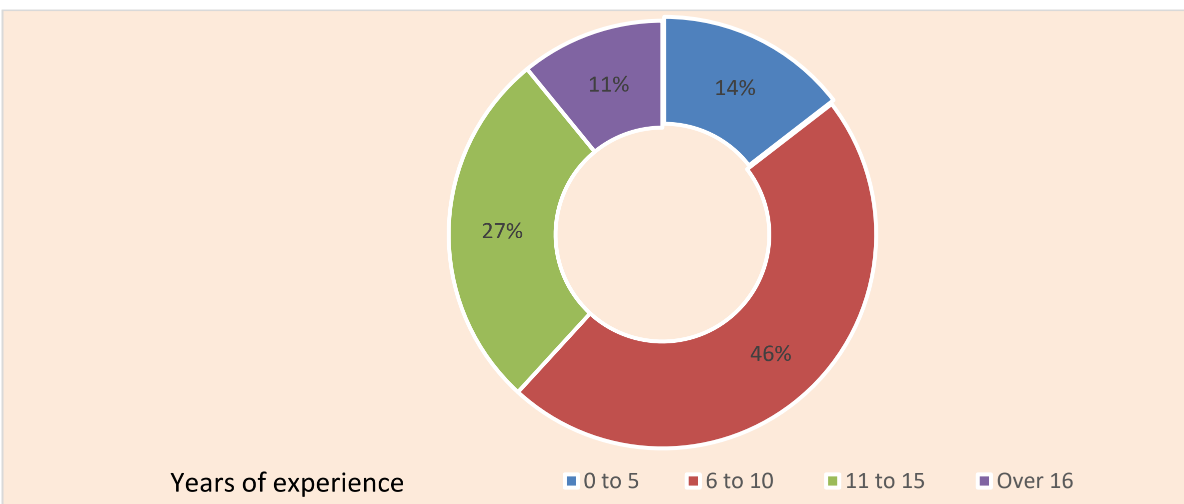

Figure 4.1: Experience of respondent in Current Organisation

4.3.1.2 Response rate by Job Title

The current study's targeted respondents who were managers in their organisations. Hambrick's upper Echelon theory (2007) suggest that organisations' performance is shaped by top management and hence best suited for this study. Majority of the respondents turned to be finance managers at 42% followed by operation managers at 20%. The results indicate data quality was enhanced by the position and role of respondents participating in the survey. The job profiles are presented in Figure 4.2.

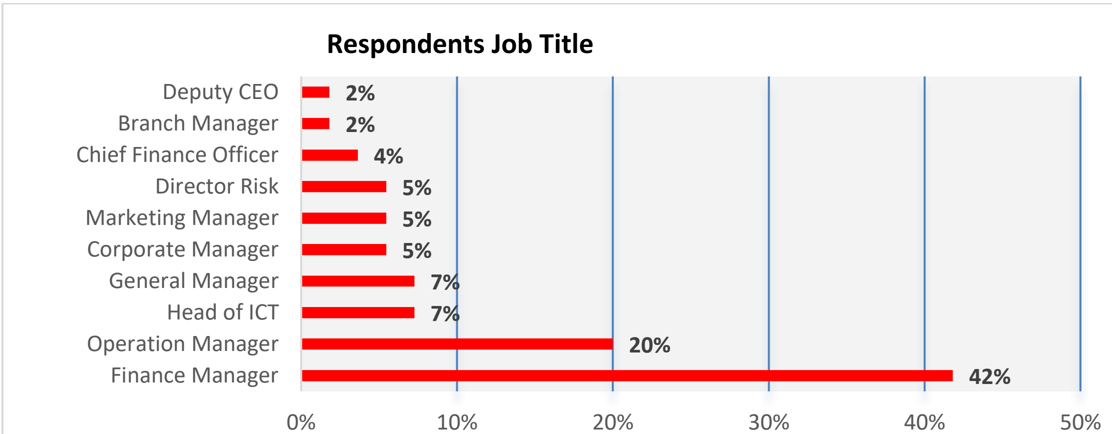

Figure 4.2: Respondents Job Title

4.3.1.3 Response rate by Industry

Preliminary data analysis revealed most respondents were from the commercial sector, which accounted for 25% of all responses. This was followed by banking sector that achieved 18%. Insurance and manufacturing sector tied at 11%. The results are presented in Table 4.1. Every sector of firms listed on the NSE responded. It implies that the study's findings can be generalized to other businesses.

Table 4.1 Response Rate by Industry

Industry	Frequency	Percent
Commercial	14	25
Banking	10	18
Insurance	6	11
Manufacturing	6	11
Agricultural	5	9
Investment	5	9
Construction	4	7
Energy	3	5
Automobile	1	2
Telecommunication	1	2
Total	55	98

4.3.1.4 Response rate by BI tool in use

The respondents were requested to indicate the BI tool in use in the current organisation they work for. In reference to the results presented in Figure 4.3, the prevalent application in use is the Microsoft Power BI at 52%. Power BI is relatively inexpensive, and therefore, more popular (Yiu et al., 2021). Additionally, Power BI desktop to version is free. Oracle analytics server ranked second at 13%. 11% of the respondents use Tableau**.** All firms that the researcher contacted had rolled out BI applications, thus increasing the reliability of the findings in reference to the study's objectives.

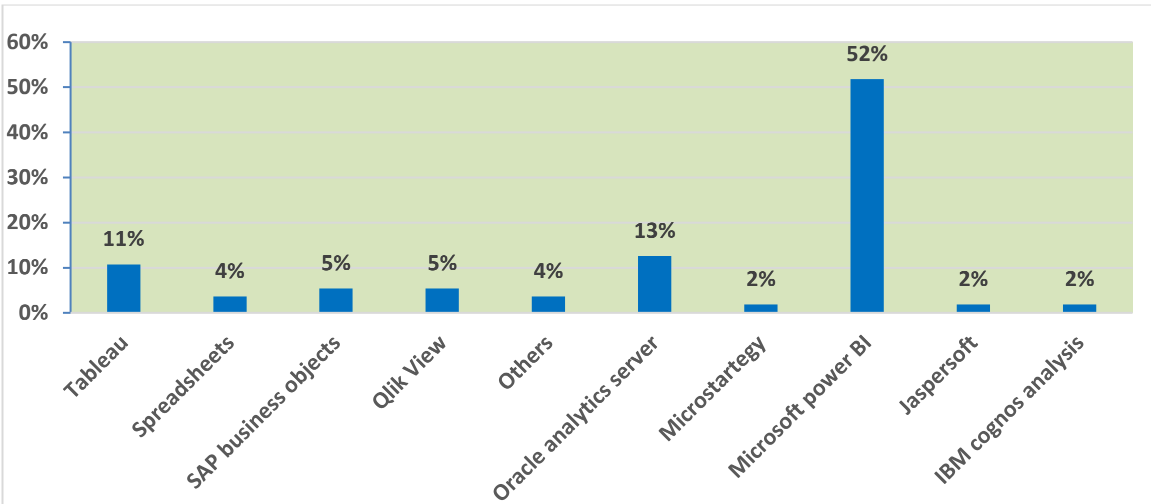

Figure 4.3: BI tool in use

4.4 Reflective Measurement Model Assessment

The external model contains indicators and a pathway that connects them to the related constructs. Hair et al. (2014) observed that reflective indicators are connected to a construct through loadings hence, the need to verify the reliability and validity of the outer model. Reliability is evaluated by estimating construct internal reliability, while convergent and discriminant tests are used to assess validity (Hair, Ringle & Sarstedt, 2011).

4.4.1 Indicator loadings

Loadings constitute the indicator's absolute contribution to its latent variable definition. A researcher begins in a reflective model by analysing the indicator loadings (also known as measurement loadings). This process is similar to factor analysis. Data is standardized in SmartPLS so that the loading of indicators varies from 0 to 1. Hair et al. (2014) argues that indicators with outer loads between 0.40 and 0.70 should only be considered for removal from the scale if removal of that indicator leads to improved composite reliability. Consequently, as indicated in section 3.4.11.2, any measures with loads below 0.60 was dropped one at a time, thereafter the assessment done for every run until only those with loads above 0.60 remained. Assessment was carried out continuously because loadings of other indicators change every time an indicator is dropped.

4.4.2 Indicator reliability

Reliability of indicators was achieved by dropping any measurement item with loads below 0.60, as indicated above. Figure 4.4 shows the original model's indicator loadings. Appendix VII details all retained and dropped indicators. In this study, the BI capability construct originally had 42 measures, 31 measures were dropped leaving only 11 indicators with loads of 0.60 and above. Effectively, four BI dimensions (data type, data reliability, flexibility and human capital) were excluded from re-specified model. All measures under these dimensions were below the threshold. Organisational capabilities initially had 10 items, 3 were dropped leaving 7 measures. Complementary resources construct had 23 measures originally, but 14 were dropped leaving 9 measures. The dependent construct of firm performance had 19 items, 12 were dropped leaving 7. Figure 4.6 displays revised SmartPLS structural equation model after dropping the loading indicators below 0.60 respectively.

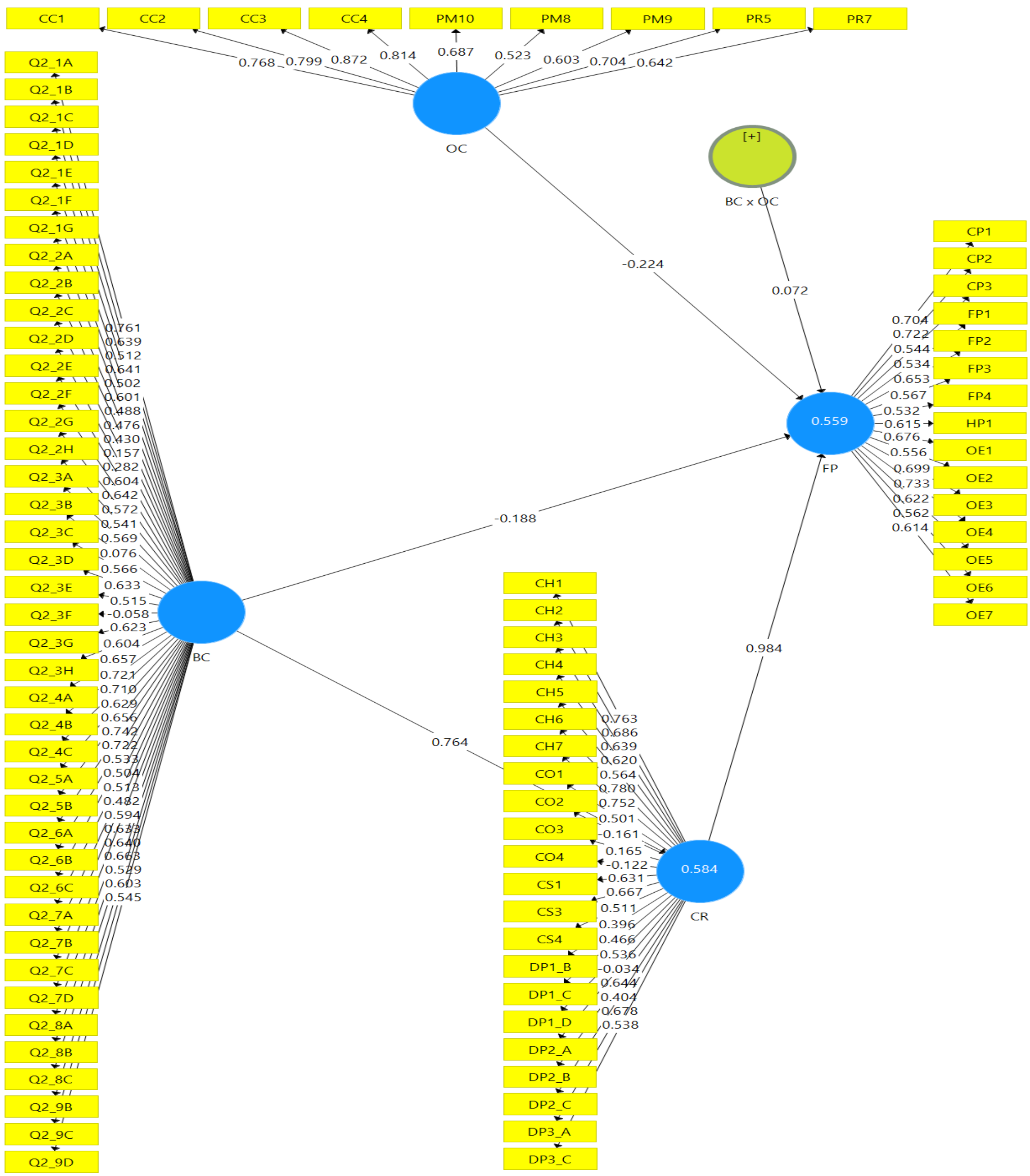

Figure 4.4 Initial Model with all Indicators

Source: Primary Data (2020)

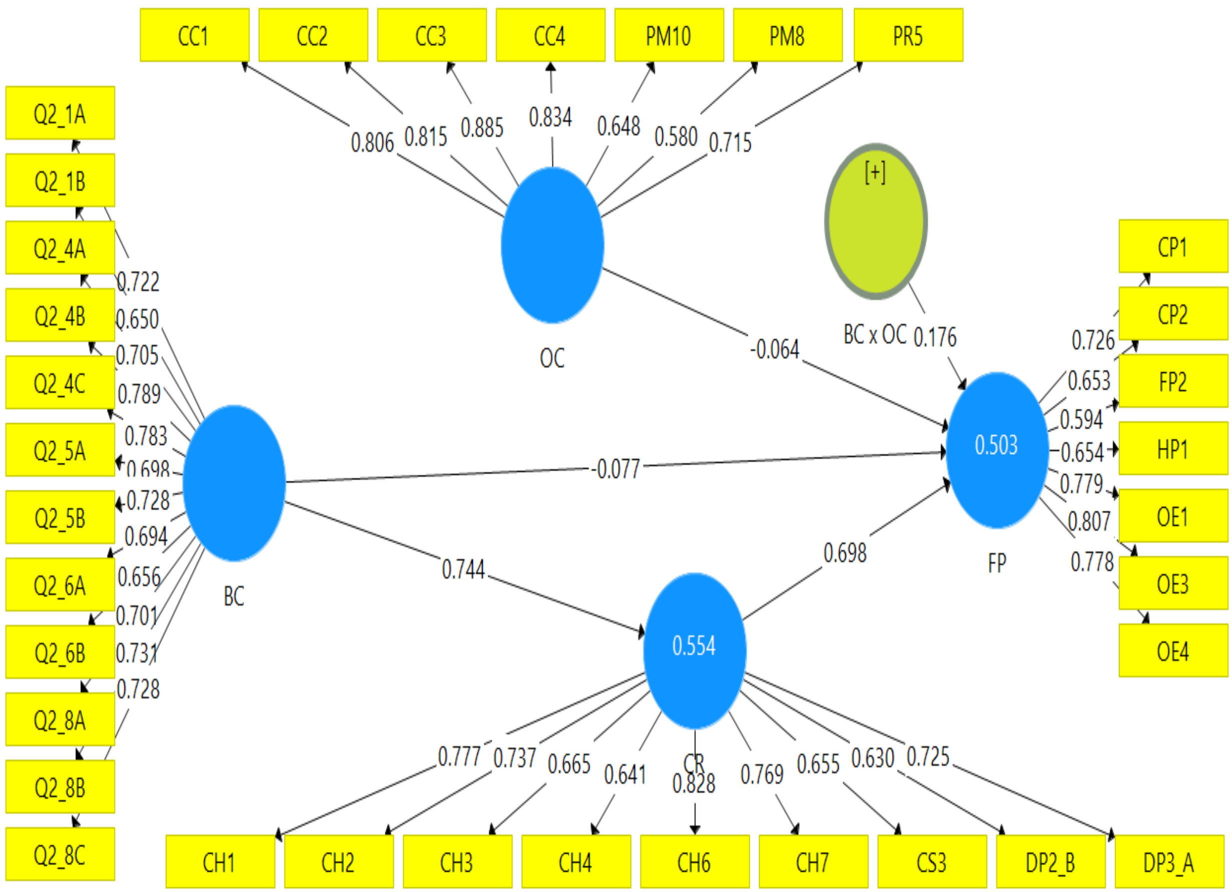

Figure 4.5 Final specified model

Source: Primary data (2020)

4.4.3 Construct Internal Consistency Reliability

The standard test for internal consistency is Cronbach's alpha, which provides a reliability estimate based on the observed indicator variables' inter-correlations. However, Hair et al. (2017) recommended the use of composite reliability because the alpha of Cronbach is sensitive to the number of items in the scale and tends to underestimate the reliability of internal consistency. In exploratory research, the authors specified that composite reliability values between 0.60 to 0.70 are adequate. According to Sekaran (2003), the reliability value of 0.7 or more, is satisfactory.

The findings of the current study's composite reliability were as follows; BI capability 0.926, complementary resources 0.904, financial performance 0.880 and organisational capabilities 0.906. These surpassed the minimum 0.7 criteria. It suggests high levels internal consistency reliability for all four constructs. The results for traditional Cronbach alpha are also presented as follows; BI capability 0.914, complementary resources 0.880, financial performance 0.843 and organisational capability 0.877. The findings are very close to those of the composite reliability tests, further confirming high level of internal consistency reliability. The results are presented in Figure 4.7 and Table 4.2.

Table 4.2 Construct Internal Consistency Reliability

Construct	Cronbach's Alpha
BI Capability (BC)	0.914
Complementary Resources (CR)	0.880
Financial Performance (FP)	0.843
Organisational Capabilities (OC)	0.877

Graphical representation of composite reliability is shown in figure 4.7 below.

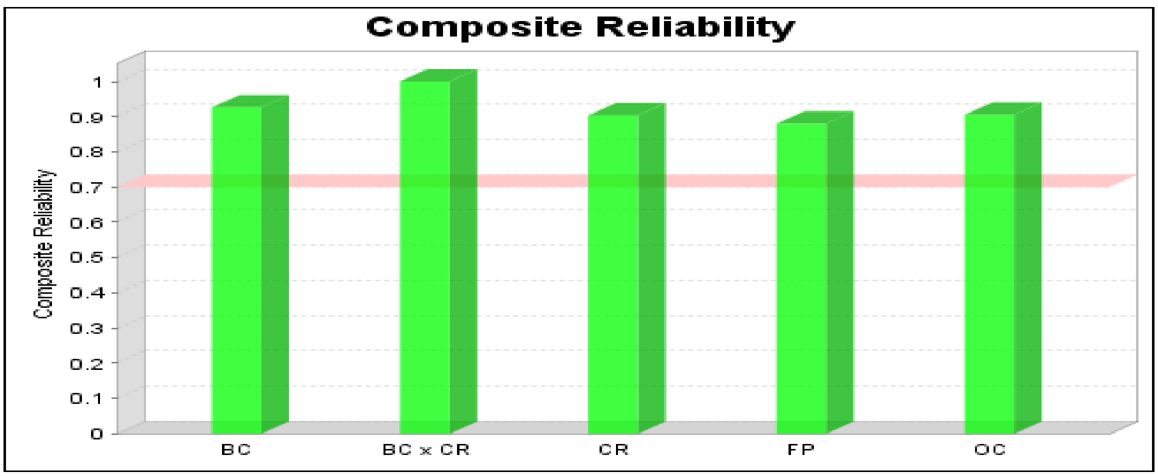

Figure 4.5 Graphic presentation of composite reliability

Source: Primary data (2020)

4.4.4 Convergent Validity

The Average Variance Extracted (AVE) of each latent variable was assessed to verify convergent validity. The AVE value is determined by generating squared loadings of a set of indicators. Convergent validity is confirmed when AVE values are greater than the acceptable threshold of 0.5 (Wong, 2013; Hair et al., 2017; Fornell & Larcker, 1981).

The AVE values for the current study are listed in Table 4.3 and Figure 4.8. The AVE value for all constructs ranged from 0.507 to 0.592, above the acceptable value of 0.5. Hence, the respecified model has satisfactory convergent validity.

Table 4.3 Average Variance Extracted (AVE)

Construct	Average Variance Extracted (AVE)
BI Capability	0.513
Complementary resources	0.513
Firm performance	0.514
Organisational capabilities	0.582

Graphical representation of Average Variance Extracted (AVE) is shown in figure 4.7 below.

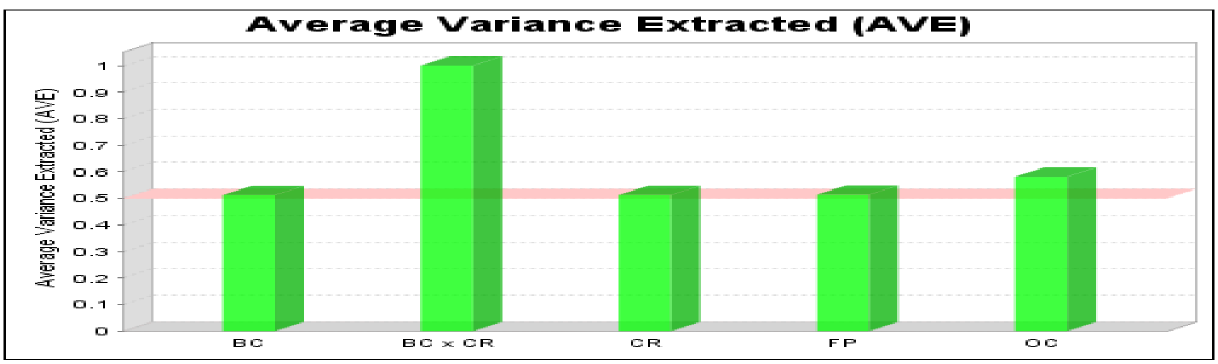

Figure 4.6 Graphic presentation of AVE

Source: Primary data (2019)

4.4.5 Discriminant Validity

The Fornell and Larcker (1981) criterion is one technique for evaluating the presence of discriminating validity. In this study, the Fornell and Larcker criterion discriminant validity for firm performance, complementary resources and organizational capability was confirmed. However, for BI capability as indicated in Table 4.4, discriminant validity was not confirmed. For example, the cross loading figure for organization capability (0.788) was greater than the square root of the AVE value of BI capability. Therefore, the cross loading criterion (Hair et al., 2014) was applied as an alternative to test discriminant validity.

Table 4.4 The Fornell and Larcker Criterion Results

	BI Capability	Complementary resources	Firm performance	Organisational capability
BI Capability	**0.716**			
Complementary resources	0.738	**0.716**		
Firm performance	0.455	0.681	**0.717**	
Organisational capability	0.788	0.713	0.420	**0.763**

Source: Primary data (2019)

Cross loadings technique requires the loads of each indicator on its construct to be greater than the cross loads on other constructs (Hair et al., 2014). As per the results of the analysis shown in Table 4.5, all indicator loadings were greater than cross loadings. This indicated that the model satisfies the discriminating validity criteria.

Table 4.5 Cross loadings Results

Items	BC	CR	FP	CR
CC1	0.733	0.193	0.539	**0.831**
CC2	0.631	0.321	0.544	**0.816**
CC3	0.646	0.437	0.592	**0.874**
CC4	0.510	0.396	0.604	**0.806**
PM10	0.447	0.174	0.510	**0.658**
PM8	0.559	0.233	0.418	**0.603**
PR5	0.628	0.350	0.643	**0.712**
CH1	0.537	0.443	**0.776**	0.483
CH2	0.484	0.408	**0.732**	0.531
CH3	0.431	0.521	**0.677**	0.551
CH4	0.453	0.483	**0.653**	0.402
CH6	0.641	0.432	**0.812**	0.677
CH7	0.627	0.498	**0.754**	0.685
DP2_B	0.515	0.384	**0.621**	0.480
DP3_A	0.494	0.613	**0.743**	0.330
CS3	0.572	0.515	**0.656**	0.560
CP1	0.244	**0.729**	0.254	0.089
CP2	0.175	**0.656**	0.364	0.216
FP2	0.223	**0.598**	0.454	0.207
HP1	0.128	**0.655**	0.424	0.171
OE1	0.412	**0.778**	0.592	0.336
OE3	0.521	**0.804**	0.630	0.431
OE4	0.428	**0.774**	0.519	0.413
Q2_1A	**0.725**	0.349	0.583	0.605
Q2_1B	**0.665**	0.330	0.480	0.611
Q2_4A	**0.694**	0.338	0.561	0.484
Q2_4B	**0.791**	0.392	0.561	0.661
Q2_4C	**0.782**	0.418	0.558	0.590
Q2_5A	**0.689**	0.148	0.406	0.394
Q2_5B	**0.724**	0.123	0.554	0.534
Q2_6A	**0.673**	0.284	0.508	0.395
Q2_6B	**0.648**	0.289	0.428	0.447
Q2_8A	**0.704**	0.492	0.590	0.628
Q2_8B	**0.740**	0.364	0.547	0.647
Q2_8C	**0.740**	0.209	0.502	0.616

Source: Primary data (2020)

However, recent studies have demonstrated that cross loads approach and the Fornell-Larcker criterion does not reliably detect discriminating validity (Henseler, Ringle, &Sarstedt, 2015). Hair et al. (2017) observed cross-loadings approach fails to demonstrate a lack of discriminating validity when two constructs are completely correlated, while Fornell-Larcker criterion executes poorly, particularly if the indicator loadings of the construct under review vary slightly. Henseler et al. (2015) suggested an alternative technique to evaluate discriminant validity based on the multitrait-multimethod matrix known as the heterotrait-monotrait correlation ratio (HTMT). Discriminatory validity is established when HTMT value is below 0.90 (Garson 2016; Henseler et al. 2015). As indicated in Table 4.6, discriminating validity for all pairs of latent constructs was confirmed.

Table 4.6 Heterotrait Monotrait Ratio

	BC	CR	FP	OC
BC				
CR	0.816			
FP	0.478	0.734		
OC	0.852	0.834	0.433	

Source: Primary data (2020)

4.4.6 Multicollinearity in the Measurement Model

Multicollinearity occurs where there is high correlation among the latent exogenous constructs. Garson (2016) noted that multicollinearity increases standard errors, renders significant assessment of independent variables unreliable and prevents the investigator from determining the relative value of one independent in reference to other variables. Garson (2016) pointed multicollinearity is not an area of concern in the reflective measurement system since latent variables are patterned as a sole predictor of observable variables. For the structural model, however, multicollinearity tests are required as discussed in the following section.

4.5 Inner Model (Structural Model) Assessment

Assessment of the hypothesized relationship within the inner model begins after confirmation of the external model's reliability and validity (Hair et al., 2014). Hence, reliability of the structural model depends entirely on the quality of the measurement model. The assessment enables the researcher to accept or reject the structural model's hypothetical proposals that represent the conceptual model. This encompasses scrutinizing the model's predictive capabilities as well as the relationships between the constructs (Hair et al., 2017). The outcomes of the measurement model assessment met the requirements for validity and reliability.

4.5.1 Goodness of Fit for the Structural Model

PLS-SEM does not have a universally acceptable goodness of fit measure (Hair at el., 2017). The use of GoF's has been challenged by Henseler and Sarstedt (2013) empirically and conceptually. Thus PLS-SEM researchers use measures that demonstrate the predictive power of the model to determine the quality of the model. The model is evaluated in terms of how well endogenous variables are predicted. Hair et al. (2017) specified that the main criteria for evaluation of the PLS-SEM structural model is the significance of path coefficients, the level of the R^2 values, the f^2 effect size, the predictive relevance Q^2, and the q^2 effect size discussed below. However, the model was first assessed for collinearity issues, as indicated in section 3.4.12.

4.5.2 Multicollinearity in the Structural Model

This phase is required to mitigate the effect of bias between independent variables when there is collinearity. PLS- SEM structural models have the potential for multicollinearity regardless of whether they are formative or reflective (Garson, 2016). To evaluate collinearity, the researcher applied the same measure used in formative measurement models: variance inflation factor (VIF) proposed by Hair et al. (2017). It offers an index that calculates how much the variance of an estimated regression coefficient rise as a result collinearity. A well-fitted model without multicollinearity should have less than 5.0 VIF coefficients (Garson, 2016). Table 4.7 displays the VIF values resulting from this study. All the VIF values were below 5 for the predictor constructs, suggesting absence of multicollinearity.

Table 4.7 Variance Inflation Factor

	BC	CR	OC	FP
BI Capability (BC)			1	2.916
Complementary resources (CR)				2.883
Firm performance (FP)				
Organisational capabilities (OC)				2.904

Source: Primary data (2019)

4.5.3 The path coefficients

Estimates for the structural model relationships are extracted after running the PLS-SEM algorithm and bootstrapping process and include beta (β) value, coefficient of determination R^2 , standard deviation, t-values and p-values (Wong, 2013). Standardized path coefficient, beta (β) was generated after running PLS-SEM algorithm. The β denotes the predicted variance of dependent construct due to a unit change in independent construct. Values of β for each path were calculated in the hypothesized model. The higher the β value, the greater the exogenous latent construct's effect on the latent endogenous construct (Hussain et al., 2018). The path coefficients have standard values ranging from -1 to + 1 (Hair et al., 2014). Estimated coefficients near + 1 signify powerful positive relationships. The nearer the coefficients estimated are to 0, the weaker the relationships.

Bootstrapping was also conducted to obtain standard error to enable researcher test for significance by computing empirical t-values and p-values for all coefficients of the structural path. Critical value for two-tailed tests used in the study was 1.96 (significance level = 5%). It was concluded that the coefficient is statistically significant if the empirical t-value is larger than the critical value. The study also used p-values to evaluate significance levels of each relationship. For the relationship under consideration to be significant at 5% level, the p-value generated had to be less than 0.05.

4.5.4 Predictive Power (R^2)

The R^2 is a measure of the predictive accuracy of the model and is computed as the squared correlation between the actual and expected values of a particular endogenous construct. The measure generates insights into the predictive power of a model (Benitez, Henseler, Castillo & Schuberth, 2019). The R^2 value ranges from 0 to 1. The higher the number, the more the predictive power (Hair et al., 2017). As a general thumb rule, R^2 values of 0.75, 0.50, or 0.25 may be defined as significant, moderate, or weak, respectively (Hair et al., 2017; Garson, 2016).

There are two endogenous latent variables in this analysis, firm performance and complementary resources. As shown in Table 4.8, predictive power on firm performance was; R^2=0.503, t-value = 6.476, p-value = 0.000 at the significant level of (t =1.96, P<0.05). This indicates that 50.3% of change in firm performance can be explained by BI capability, organisation capability and complementary resources. For complementary resources, the results were; R^2 =0.554, t-value =5.971 and p-value = 0.000 at the significance level of (t =1.96, P<0.05). The results imply that 55.4% variation in complementary resources can be explained by BI capability. The results are statistically significant. The model's predictive power is moderate for both firm performance and complementary resources based on the categorisation by Hair et al. (2017) and Garson (2016).

Table 4.8 Predictive Power R^2

	Predictive power (R^2)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Complementary resources	0.554	0.093	5.791	0.000
Firm performance	0.503	0.078	6.476	0.000

Source: Primary data (2019)

4.5.5 Effect size (f^2)

The Cohen's f^2 measure evaluates how strongly an exogenous construct helps to explain identified endogenous construct in relation to R^2. The effect size is computed as f^2 =

$(R^2_{Included} - R^2_{Excluded})/R^2_{Included}$ (Hair et al., 2017). $R^2_{Included}$ is the R^2 values when exogenous variable is included, while $R^2_{Excluded}$ is the R^2 value when exogenous variable is excluded. According to Cohen (1988), the criterion for assessing f^2 is that values of 0.02, 0.15, and 0.35, represent small, medium, and large effects respectively. Based on the value extracted as indicated in Table 4.9, BI capability has large predictive power on complementary resources (f^2 value of 1.242). Complementary resources as well has large predictive power on firm performance (f^2 value of 0.340). However, Organisational capability has a small predictive power on firm performance (f^2 value of 0.003).

Table 4.9 Effect size (f^2)

	Complementary resources	Firm performance
BI Capability	1.242	0.004
Complementary resources		0.340
Moderation (BC x CR)		0.082
Organisational capabilities		0.003

Source: Primary data (2020)

4.5.6 Cross-validated redundancy (Q^2).

Stone-Geisser's Q^2 is a metric to test the inner model's predictive relevance by conducting the blindfolding procedure. Blindfolding is a sample reuse method that systematically removes data points and gives an estimate of the initial values. Unused data in the model estimation is predicted accurately when PLS path model shows predictive relevance. The test is based on a method of sample reuse, that omits a portion of the data matrix, estimates model parameters and predicts the omitted portion using estimates (Hair et al., 2014). There are two approaches for computing Q^2; construct crossvalidated redundancy and construct crossvalidated communality (Hair et al., 2017). This study adopted construct crossvalidated redundancy approach in reference to the recommendation by Hair et al. (2017), because it involves the structural model (the path model's main component) to predict discarded data points.

According to Chin (1998), Q^2 values greater than 0 indicate that the model has predictive relevance to a specific endogenous construct. The values 0 and below, on the other hand, indicate a lack of predictive significance. The current study resulted in complementary resources Q^2 value of 0.258 and firm performance value of 0.209 presented in Table 4.10. Hence, the model shows a fairly high degree of predictive relevance for endogenous constructs (that is, complementary resources and firm performance).

Table 4.10 Cross-validated redundancy (Q^2)

	SSO	SSE	Q^2 (=1-SSE/SSO)
Complementary resources	495	367	0.258
Firm performance	385	304	0.209

Source: Primary data (2019)

4.5.7 The q^2 effect size

The q^2 effect size is an alternate statistic used to evaluate the relative predictive relevance to the endogenous construct of a given exogenous construct. This measure compares Q^2 predictive relevance values of models when specific exogenous construct has been left out. The q^2 values of 0.02, 0.15, and 0.35, respectively, indicate that an exogenous construct has a small, medium, or large predictive relevance for a certain endogenous construct (Hair et al. (2017). As indicated in Table 4.11 below, the q^2 effect size for BI capability, complementary resources and organisational capabilities was 0.01, 0.09 and 0.02 respectively. The results indicate complementary resources has the biggest q^2 effect size value at 0.09, implying that the omission of this construct has a medium effect on the predictive relevance than BI capability and organisational capabilities.

Table 4.11 q^2 effect size

	q^2 effect size
Omission of BI Capability (BC)	0.01
Omission of Organisational capabilities (OC)	0.02
Omission of Complementary resources (CR)	0.09

Source: Primary data (20120)

Table 4.12 below presents summary results of the evaluation of the structural model. The model has moderate predictive power as wells as high degree of predictive relevance.

Table 4.12

Latent variable	**R^2**	**R^2 Change: (f^2)**	**Q^2**	**Q^2 change (q^2)**
BC, CR, OC, FP	FP= 0.503		0.258	
	CR=0.554		0.209	
Omission of BC		1.242	0.202	0.01
Omission of CR	0.357	0.340	0.139	0.09
Omission of OC	0.458	0.003	0.192	0.02
Omission of the moderating (BC x OC)	0.410	0.082		
BC and FP	0.206	-	0.103	-

4.6 Hypotheses Testing

Analysis in structural equation modelling typically yields results for all relationships depicted in the SEM model. Figure 4.9 presents t-statistics on the structural regression model, Figure 4.10 present p-value structural regression model, and Figure 4.11 depict path coefficients and indicator loadings. The relationships resulting from PLS analysis between all variables in the SEM model is summarized in Table 4.13. Each path that connects two constructs in the current structural model represents a hypothesis stated in section 2.9. The current study applied bootstrapping with 500 resamples to measure t-statistics and P-values (Chin, 1998). This facilitated the assessment of the path coefficients statistical significance. The change effect of the coefficient determination R^2 was measured by f^2 values, while predictive relevance of the change effect of the Structural equation model was evaluated by q^2 effect size. Due to the latent variables categorized as exogenous variables in the study structural model, the change effect values were applied to measure the variations of both R^2 and Q^2 values. The path coefficients were assessed at the significance level of ($t > 1.96$, P 0.05).

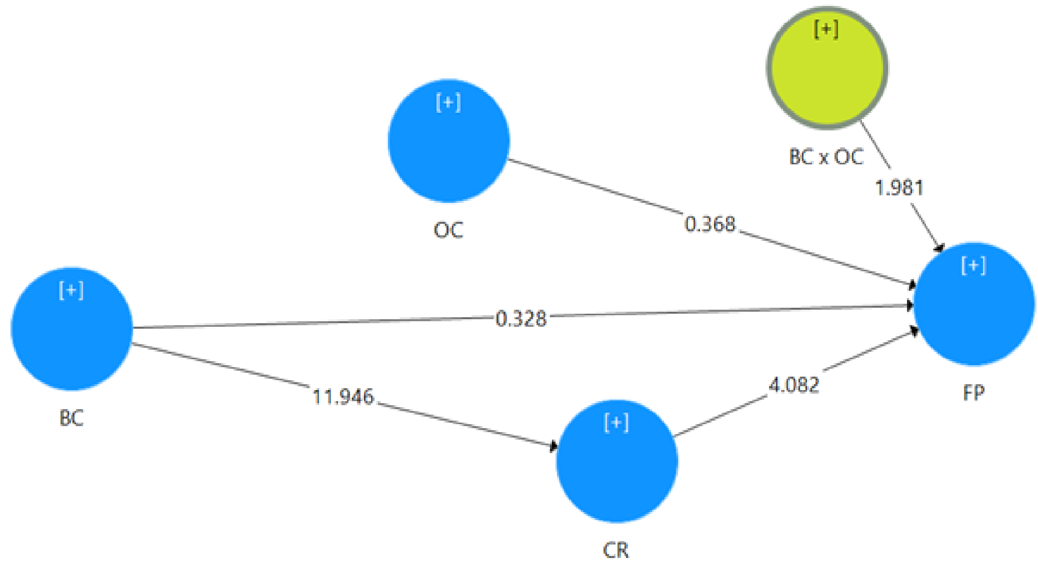

Figure 4.7 Structural Regression Model with t Statistics

Figure 4.10 below represent the p-values for all paths connecting to various constructs in the structural model

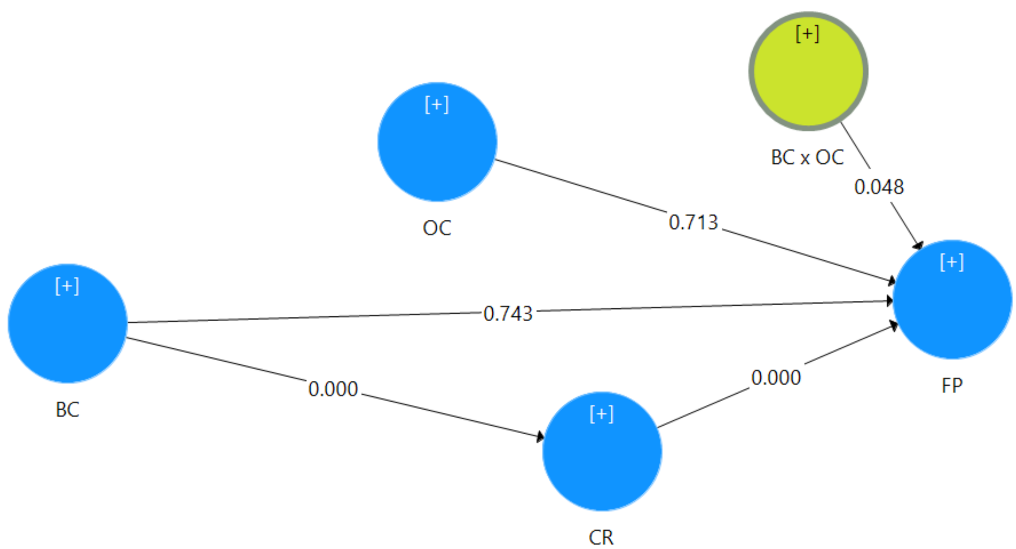

Figure 4.8 Structural Regression Model with P Values

Figure 4.11 below indicate the beta values and indicator loadings for all paths connecting to various constructs in the structural model

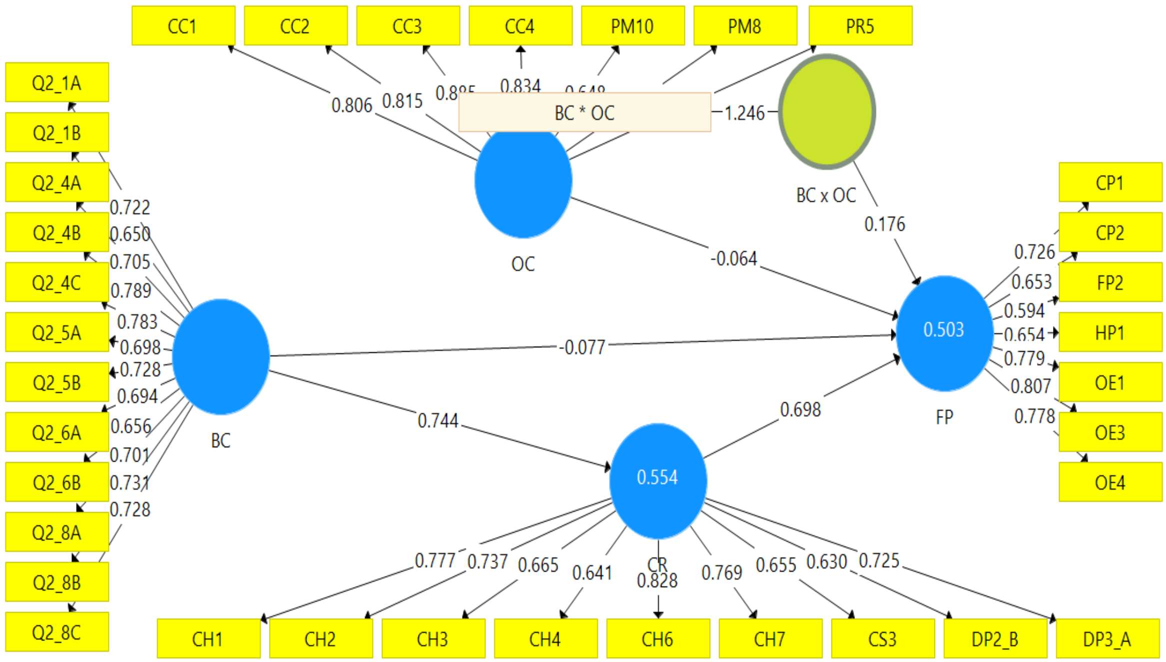

Figure 4.9 Structural Regression Model with Path Coefficient and Indicator Loadings

Source: Primary data (2020)

Table 4.13 PLS Model Path Coefficients and associated Statistics

Relationships	Path Coefficients	t-Statistics	P-Values
BI Capability (BC) →Complementary Resources (CR	0.744	11.946	0.000
Organizational Capability (OC) → Firm Performance (FP)	-0.064	0.368	0.713
BI Capability (BC) →Firm Performance (FP)	0.077	0.368	0.743
Complementary Resources (CR) → Firm Performance (FP)	0.698	4.082	0.000

4.6.1 Business Intelligence Capability, Organisational Capability, Complementary Resources and Performance of Firms listed at The Nairobi Securities Exchange.

The objective of the study was to establish the relationship between BI capability, organizational capabilities, complementary resources and performance of firms listed at the NSE. This relationship was analysed using SmartPLS 3.2.1 software. To determine both direction and strength of the relationships and the statistical significance of those relationships, path coefficients were computed and evaluated.

4.6.2 BI Capability and firm performance

Hypothesis one (H_{01}) involved checking whether a relationship exists between BI capability and firm performance. The null hypothesis (H_{01}) stated that BI capability has no effect on firm's performance. This hypothesis was tested using PLS-SEM analysis and path coefficients results were β = 0.353, t-value = 4.964 and p-value = 0.000. The predictive power results were R^2 = 0.261 and f^2 = 0.353. The results imply that BI capability can explain 26 percent of the variance in firm performance. The findings also indicate a positive relationship between BI capability and firm performance that is statistically significant. The f^2 effect size in this relationship is large. Based on the above results, at the significance level of (t >1.96, $P \leq$ 0.05), the null hypothesis is rejected. Figures 4.9, 4.10 and 4.11 indicates the β values, t-values and p-values of this relationship.

PLS-SEM: Beta value = 0.353

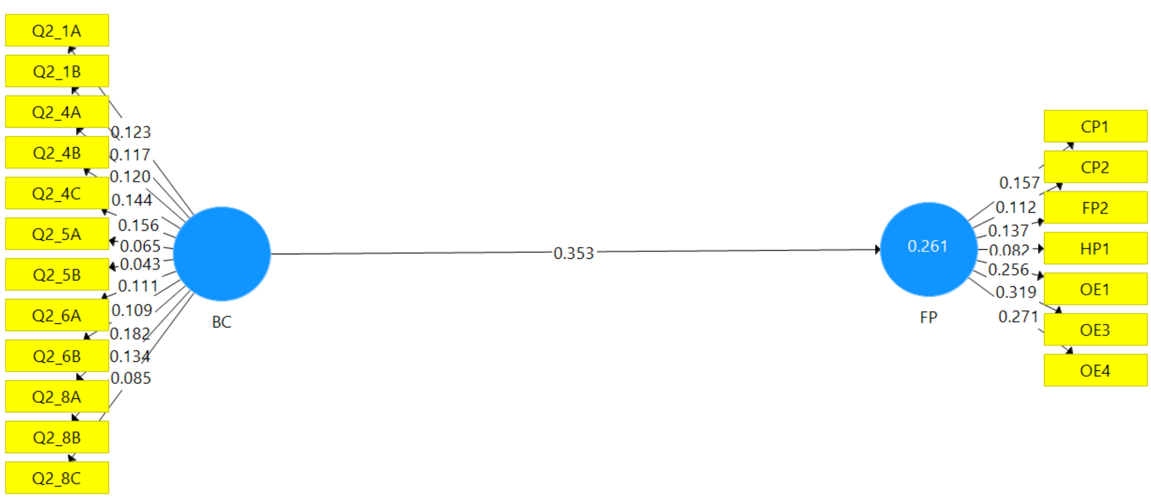

Figure 4.10 BI Capability and Firm Performance Path Coefficients, R2 and Indicator Loadings

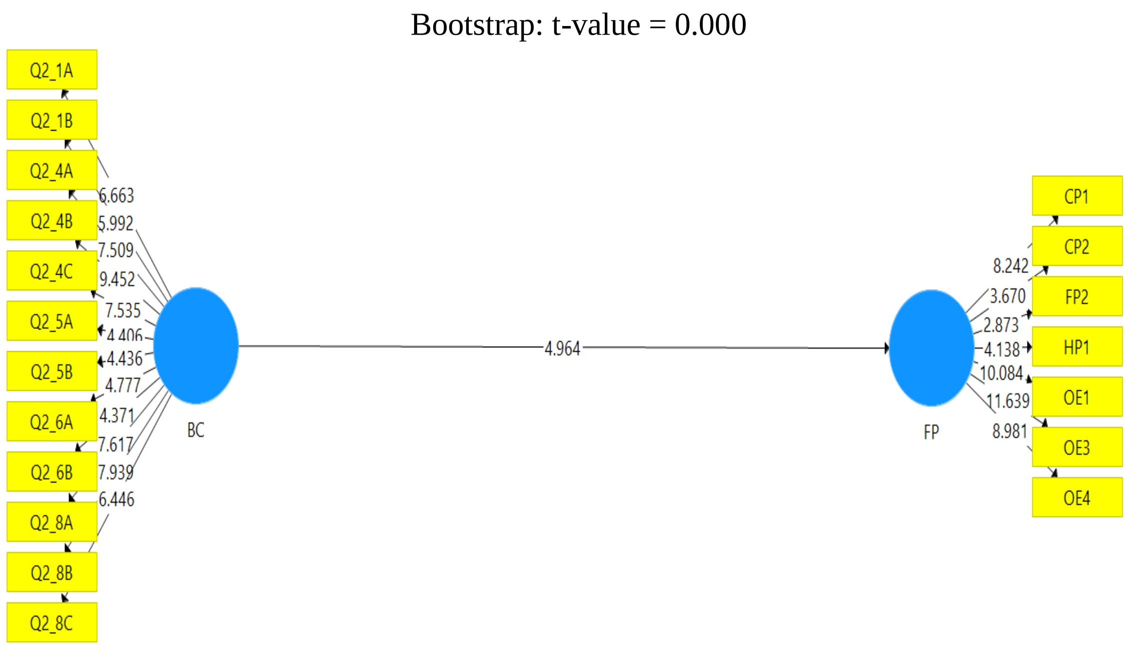

Figure 4.11 BI Capability and Firm Performance t-values

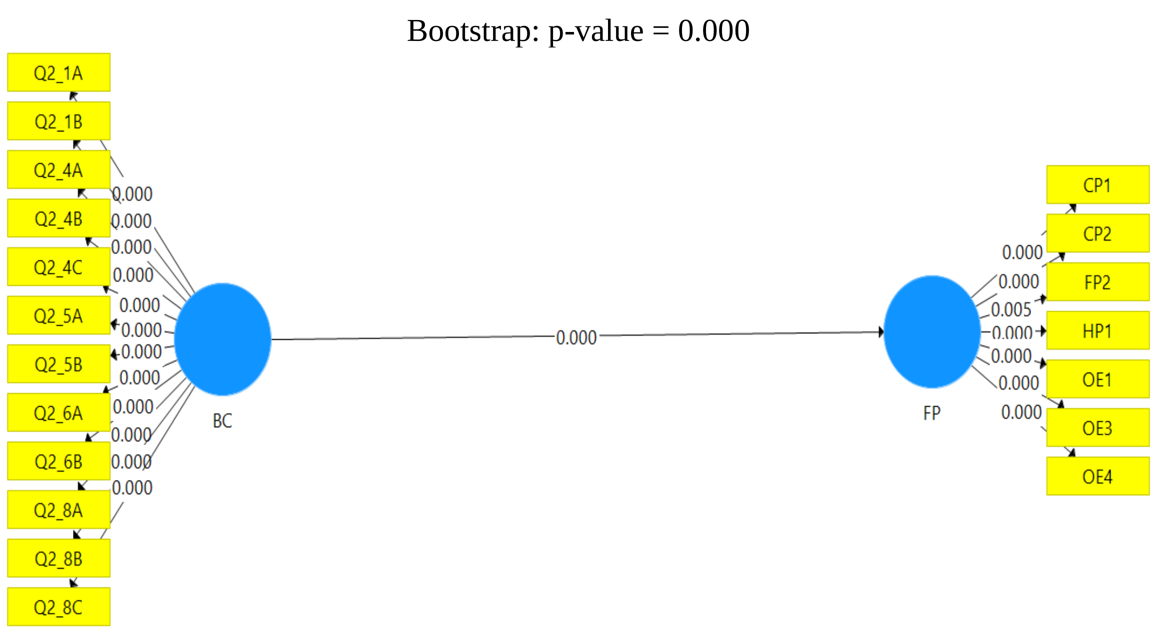

Figure 4.12 BI Capability and Firm Performance p-values

Source: Primary data (2020)

4.6.3 Mediation of Complementary resources in the relationship between BI Capability and Firm Performance.

PLS-SEM mediation is not a single process but a series of steps (Hadi et al., 2016; Wong, 2016; Hair et al., 2014; Hair et al., 2017; Nu'man et al., 2020) as described in Section 3.4.14. The mediating effect tested in this study is shown in Figure 4.15. A significant relationship between independent variable (BI capacity-BC) and dependent variable (firm performance -FP) as calculated by t-value **(A)** was envisaged. The introduction of the mediating variable (CR) is proposed to mediate the significance of the relationship between the independent variable (BC) and the dependent variable (FP) in order to produce a t-value **(B)**. The mediation effect was assessed using a four-step process (Schultheis, 2016), as shown in Figure 4.15.

Step one focused on assessing the significance and nature of the BI capability (BC) and firm performance (FP) relationship. Appendix VIII(a) results showed that there is a significant (t-value = 4.964) and a positive relationship (beta value = 0.353), suggesting that BC has an effect on FP.

Step two then tested the relationship between BI capability (BC) and a mediating variable, complementary resources (CR). Essentially CR becomes the dependent variable under this step. The finding reveals that BC has an impact on CR with the results showing that there is a significant (t-value = 12.523) and a positive (beta = 0.746) relationship between these two constructs as shown in Appendix VIII(b).

Step three was to test the effect of the mediating variable CR on the dependent variable FP. The findings showed that there is a significant (t-value = 12.583) and a positive (beta = 0.683) relationship between CR and FP as indicated in Appendix VIII(c).

Step four evaluated the influence of the mediating variable on the relationship between BC and FP. It was found that the relation between the independent variable, BC and the dependent variable, FP, was affected by the introduction of the mediating variable, CR. The relationship between BC and FP was mediated to the extent that the relationship (β = -0.103) was no longer significant (t-value = 0.484 which is confidence < 1.96 @ 95%

confidence). However, the indirect bath between BC, FP and mediating variable CR was significant and positive (β = 0.558, t-value = 3.600, p-value = 0.000, $R^2 = 0.458$ and $f^2 = 0.36$). Meanwhile, the path between mediating variable CR and FP remained positive and significant (t-value = 4.434, p-value 0.000 and β = 0.750) as shown in Appendix VIII(d).

The result also complies with conditions set by Baron and Kenny (1986) that state:

"(a) the independent variable must have an effect on the dependent variable;
(b) the independent variable must have an effect on the intervening variable(s); and
(c) intervening variable(s) must affect the outcome, after controlling for the independent variable. To establish full mediation, the total effect of the independent variable on the outcome must become non-significant in the presence of the intervening variable(s), while the indirect effect is significant. Partial mediation is established when the path remains significant but is substantially reduced and the indirect effect is significant" (Baron and Kenny 1986, as quoted in Schultheis 2016, p.84)

The next phase was to determine the magnitude of mediation impact. This was done by determining variance accounted for (VAF). According to Hair et al. (2014), VAF below 20% indicate no mediation, between 20% and 80% indicate partial mediation. VAF above 80% implies full mediation. The VAF formula is shown below.

VAF = Indirect effect/Total effect.

Total effect is a summation of Indirect effect plus direct effect.

In the current study, VAF is 0.558/(0.558+ 0.353) = 61%.

This shows that the mediation magnitude was partial at about 60%. Therefore, the conclusion based on the findings is that the relationship between BC and FP is partially driven by CR. Hence, the null hypothesis (**H_{02}**) that complementary resources have no mediating effect on the relationship between BI capability and firm's performance is rejected.

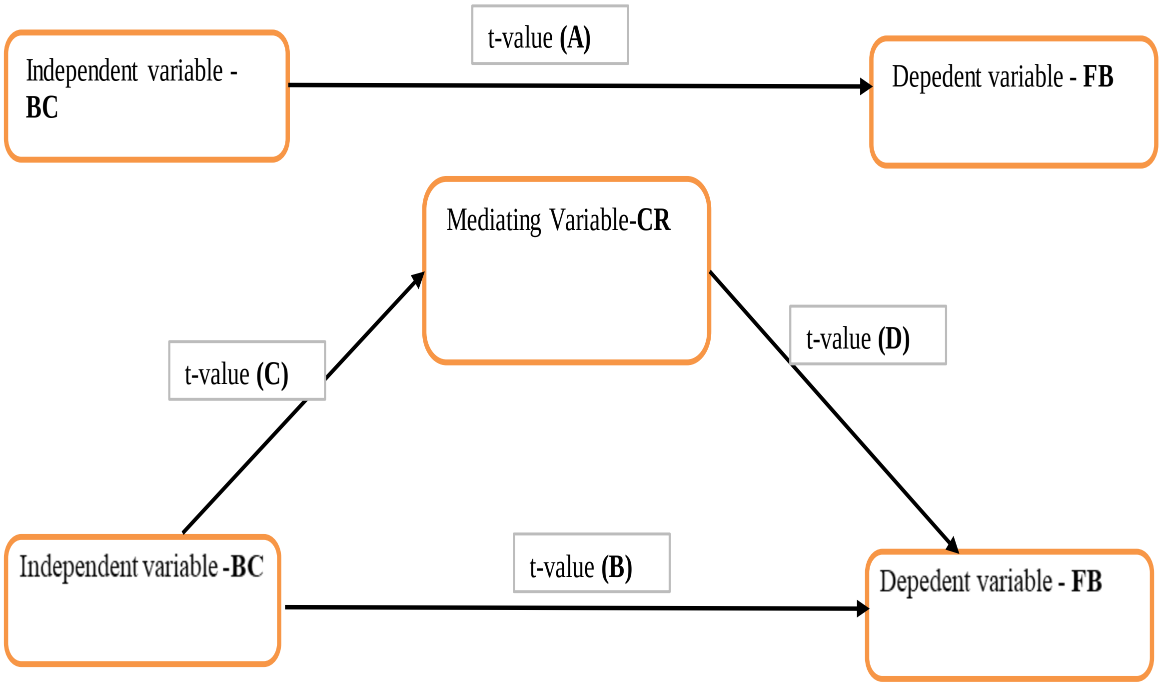

Figure 4.13 Mediation process (Adopted from MacKinoon, 2007; Sobel, 1990 and Schultheis, 2016).

Mediation results presented in Appendix VIII(a) to Appendix VIII(b) is summarized in table 4.14.

Table 4. 14 Mediation effect testing summary

Test	**model**	**Beta value (Standard regression weight)**	**t-value (test for significance >1.96 @ 95% confidence level)**
Independent -> Dependent	BC -> FP**(Step1)**	0.353	4.964
Independent -> Mediating (Mediating Variable treated as Dependent Variable)	BC ->CR**(step2)**	0.746	12.523

Mediating -> Dependent (Mediating Variable treated as Independent Variable)	CR-> FP**(step3)**	0.683	12.583
Independent -> Dependent (With Mediating Variable impacting)	BC -> FP (**Step4**) *Indirect effect* BC ->CR-> FP	-0.103 0.558	0.484 3.600

Source: Primary data (2020)

In essence, complementary resources have a mediating effect on the association between firm performance and BI capability. Table 4.14 shows that with introduction of mediating variable, the path between BI capability and firm performance changes from being significant (β = 0.353, t-value = 4.964) to insignificant (β = -0.103, t-value = 0.484). Therefore, $\mathbf{H_{02}}$ is rejected.

4.6.4 Moderation effect of Organisational Capability in the relationship between BI Capability and Firm Performance

The third hypothesis stated that organisational capability has no moderating effect on the relationship between BI capability and firm performance. The two-stage method of PLS algorithm to analyse moderation effect was applied (Hair et al., 2017; Henseler & Chin, 2010). The first stage was to analyse moderating effect of organisational capability on the relationship between BI capability (BC) and firm performance (FP). The second stage was to analyse the direct effect between organisational capability (OC) and firm performance. To carry out moderation analysis in SmartPLS, interaction term labelled *moderating effect 1* was added to the model as shown in Figure 4.17. As indicated, interaction term has a positive impact of 0.252 on firm performance (FP). The results in Figure 4.17 show that the relation between BI capabilities (BC) on FP is 0.320. It implies that when organisational capability (OC) is increased by one standard deviation unit, the relationship between BC and FB, is increased by the size of the interaction term (0.320+0.252 = 0.572). Conversely, if OC is reduced by one standard deviation unit, the relationship between BC and FB becomes 0.068 (0.320 less 0.252). The following simple slope plot depicts a two-way interaction effect.

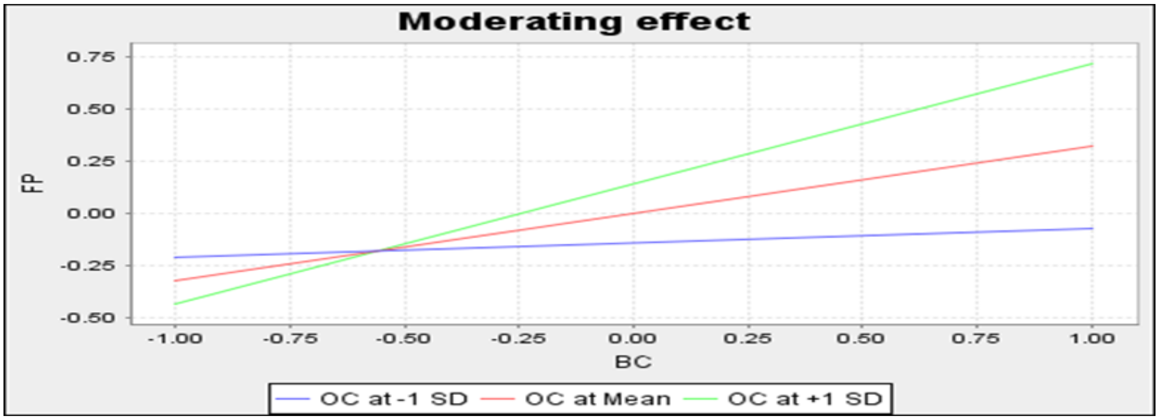

Figure 4.14: Simple slope plot on Moderating effect

The three lines shown in Figure 4.16 reflect the BC (x-axis) to FP (y-axis) relationship. The middle line reflects the relationship for a mean level effect of the moderating variable OC. The other two lines portray the association between BC and FP for average value of OC plus one standard deviation unit and mean value of OC less one standard deviation unit.

The moderation test also involved bootstrapping to test for significance and the outcomes were as follows; β = 0.252, *P*-value = 0.021, t-value = 2,302 and R^2 = 0.357. The finding for the moderated relationship of the effect size (f^2) is medium at 0. 145. The results are presented in Figure 4.17 and 4.18. The highlighted findings empirically show that at the significance level of ($P < 0.05$ and $t > 1.96$) the moderating impact of organisational capabilities is positive and statistically significant. Therefore, **H_{03}** is rejected.

The direct effect of organisational capability on firm performance presented in Figure 4.19 were as follows were as follows: β =0.445, t-value =3.590, p-value = 0.000. The predictive power (R^2) results were: R^2 = 0.198, and f^2 = 0.248. This indicates a positive and statistically significant relationship between organisational capability resources and firm performance. Furthermore, 19% of variation in firm performance can be explained by the model. f^2 effect size value of 0.23 implies that organisational capability in this relationship has medium proportion of predictive power.

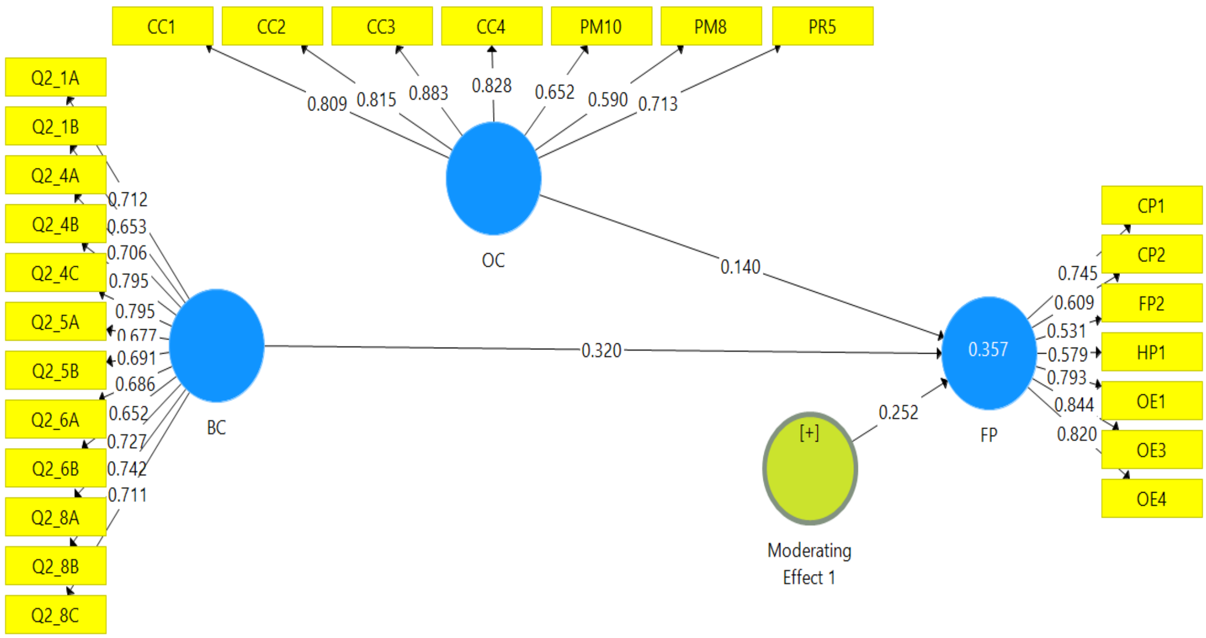

Figure 4.15 Moderation Effect of CR on the relationship between FP and BC

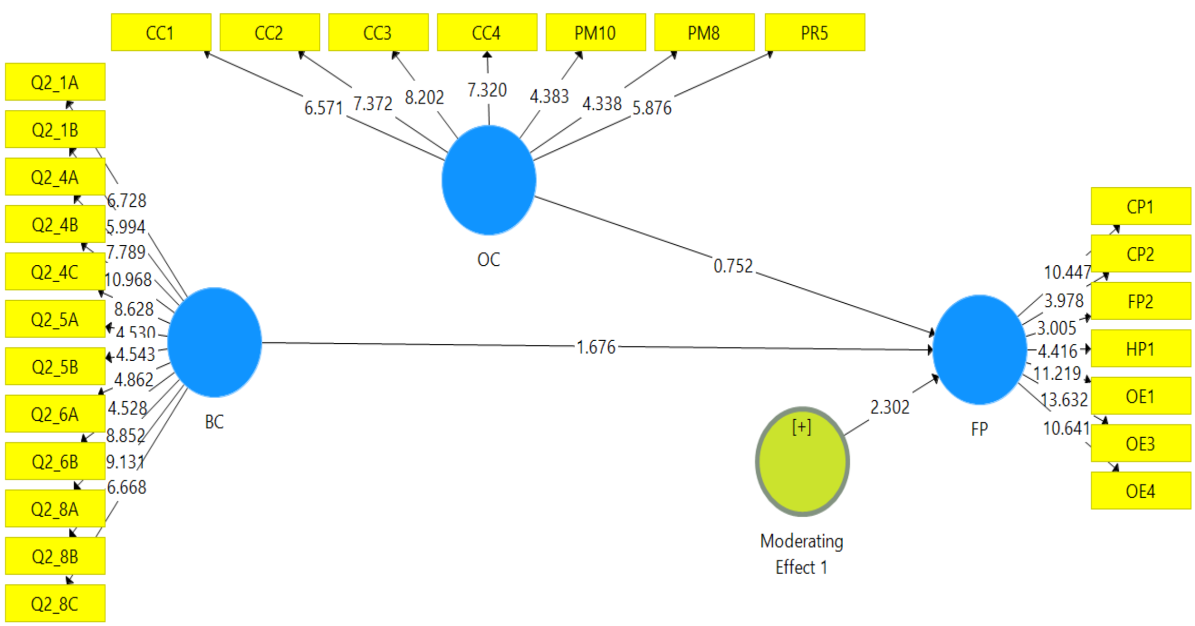

Figure 4.16: T-values for the Path Relationships

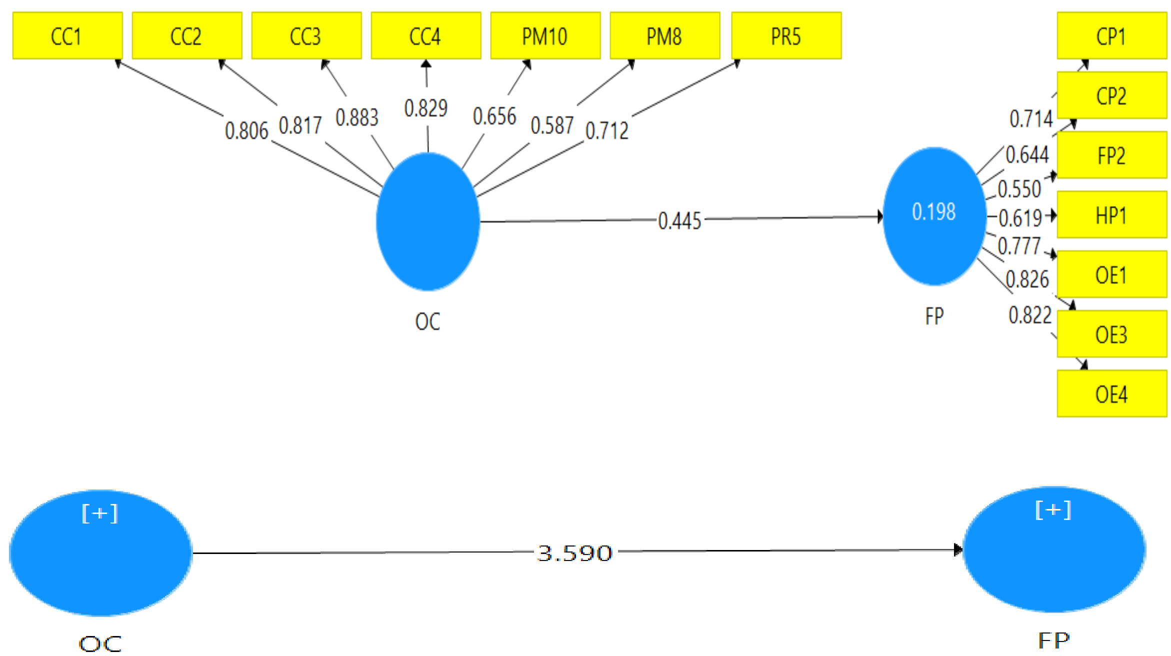

Figure 4.17:Direct Effect of CR on FP and their Indicator Loadings

4.6.5 Combined effect of BI Capability, Organisational Capability and Complementary Resources on Firm Performance

H04 proposed that BI capability, organisational capability and complementary resources have no combined effect on firm performance. Table 4.15 presents various tests conducted in this study. Exogenous construct, namely BI capability, complementary resources and organizational capability, contributed respectively to the endogenous construct's overall predictive power (R^2). Direct path between BI capability and firm performance yield predictive power of (R^2) 0.290, β = 0.353, t-value = 4.239 and p-value of 0.000. When complementary resources (mediation) was added to the model, predictive power (R^2) improved to 0.458 with a t-value of 3.600 and p-value = 0.000. A test between BI capability and organisational capability (moderated) capability generated R^2 value of 0.357, β = 0.176, p-value = 0.021 and t-value of 2.302. A further test on the direct path between organisational capability and firm performance, generated R^2 value of 0.198, β = 0.445, p-value = 0.000 and t-value of 3.590, implying positive and significant relationship.

However, when all constructs were tested jointly, the model generated a high predictive power (R^2) value of 0.503, t-value of 6.493 and p-value of 0.000. It implies that 50.3% of changes in firm performance can be explained by the model.

Table 4.15: The Model combined effect on R^2

	Std beta	T Statistics	P Values	R square
BC -> FP	0.353	4.964	0.000	0.261
BC -> CR -> FP	0.558	3.600	0.000	0.458
BC x CR-Moderated	0.176	2.302	0.021	0.357
CR-> FP	0.445	3.590	0.000	0.198
BC -> CR -> OC-> FP (joint)	0.503	6.493	0.000	0.503

Key BC= BI capability, FP= Firm performance, OC= organisational capability, CR= complementary resources

To evaluate the predictive power change effect shift and predictive relevance of each exogenous latent variable, Q^2 and f^2 values were analysed. The effect change of predictive power (R^2) for each latent variable is assessed by f^2 values whereas the effect change of Q^2 is measured by the q^2 values (Garson, 2016). Table 4.16 displays f^2 and q2 measures for the respective latent variables. Effect change on R^2 is depicted by f^2 values when the respective exogenous variable is omitted from the model. Complementary resources have large predictive power on firm performance (f^2 value of 0.340). In the current study, the Q2 values of all relationships are greater than zero, thus showing that all exogenous constructs have predictive relevance for endogenous constructs (firm performance Q^2 = 0.209 and complementary resources Q^2 = 0.253). The q^2 values reflect the variations in a model fit associated with the exclusion of corresponding exogenous variables. This parameter primarily tests the effect of the exogenous variable in the model's estimation of endogenous variables. Each of the exogenous variables q^2 values were lower than the endogenous variables' overall Q^2 values, which means that the model's predictive relevance is greater when exogenous variables are included. Findings in the current study show that the collective influence BI capability, complementary resources and organisational capability resulted in a significantly greater impact on the performance of listed firms on NSE than the individual effect as depicted in Table 4.15. Therefore, **H_{04}** is rejected. Hypotheses testing results and respective conclusion are summarized in Table 4.17

Table 4.16 The Models Change Effect Values

Variable	R^2& Q^2	BI capability	Organisational capability	Moderation	Complementary resources
Complementary resources	R^2= 0.554	f^2=1.242			
	Q^2=0.253				
Firm performance	R^2= 0.503	f^2=0.004	f^2=0.003	f^2=0.082	f^2=0.340
	Q^2=0.209	q^2=0.010	q^2=0.020		q^2=0.090

Table 4. 17 Summary of the Results of the Tests of Hypotheses

Hypothesis	Results	Remarks
BI capability has no effect on firm's performance.	β = 0.353, R^2 = 0.261, p = 0.000, t = 4.964	Positive and significant **H_{01}** Rejected
Complementary resources have no mediating effect on the relationship between BI capability and firm's performance	Indirect path: BC-> CR->FP β = 0.558, R^2 = 0.458, p = 0.000, t = 3.600 VAF=60%	Positive and significant **H_{02}** Rejected
Organisational capability has no moderating effect on the relationship between BI capability and firm's performance.	β = 0.252, R^2 = 0.357, p = 0.021, t = 2.302	Positive and significant **H_{02}** Rejected
BI capability, organisational capability and complementary resources have no combined effect on firm's performance.	BC -> FP: **R^2 = 0.261** BC -> OC -> FP: **R^2 = 0.241** BC x CR-Moderated: **R^2 = 0.357** OC -> FP: **R^2 = 0.198** BC -> CR -> OC-> FP (Joint): **R^2=0.503, Q^2 = 0.209** **t= 6.493, p=0.000**	Positive and significant **H_{04}** Rejected

4.7 Chapter Summary

The findings of quantitative data analysis are presented in this chapter based on the data collected from 55 listed companies. The chapter commenced with descriptive and covered areas such as response rate. Demographic profiles of the respondents were also presented on issues such as work experience, job title and the industry. Data preparation and coding was also highlighted. The measurement model was assessed first by dropping all indicators that did not attain the minimum threshold. Reliability of the measurement model was evaluated by estimating construct internal reliability while validity is assessed through convergent and discriminant validity.

The assessment of the structural model was done by analysing the coefficients of relationships, moderation and mediation of the constructs as reflected in the conceptual framework. The overarching fitness of the study's model was also analysed using the predictive relevance (Q^2), effect size q^2, coefficient of determination (R^2) and effect size f^2. Description of the findings of hypotheses testing was presented as outlined in chapter two. The four hypotheses were evaluated based on standard regression weights and t-values. The results did not support for the four hypotheses.

CHAPTER FIVE

QUALITITATIVE DATA ANALYSIS FINDINGS

5.1 Introduction

This section provides an analysis of qualitative data results to enhance quantitative data findings. The first segment provides demographic details of the respondents. The second segment depicts the results of the qualitative analysis and interpretation of the data.

5.2 Participants for Interview

Eight respondents were chosen based on the sectoral representation as depicted in Table 5.1. Sectors represented include banking, insurance, commercial & services, energy, agriculture and telecommunication. The Participants years of experience ranged from 8 to 25 years. Three respondents had attained a bachelor's degree, two held a master's degree, while one held a doctoral degree. The researcher carried out interviews between August and September 2019.

Table 5.1 Interviewees demographic information

Respondent	Level of education	Position	Sector	Years of Experience
B1	MBA	Finance Director	Agricultural	21
B2	PhD	IT Director	Banking	18
B3	BCOM	Relationship Manager	Telecommunication	8
B4	MBA	General Manager	Manufacturing	9
B5	BSC	Fosa Manager	Banking	14
B6	MBA	Operation Director	Commercial Services	16
B7	MBA	Financial Controller	Energy	12
B8	MSC	Managing Director	Insurance	25

5.3 Qualitative preparation

Recording of all interview sessions was done and transcribed later. To ensure consistency, all sessions of the interview were carried out by the researcher. Before commencing analysis, the researcher read through the transcribed data whilst also listening to the audio recordings, allowing for transcription errors to be corrected. Where the issues were not clear, a follow-up call was done to a respective interviewee for clarification. The edited transcribed report was then uploaded to Atlas.ti software.

All records relating to the interviewing process were placed in a single folder and later uploaded into Atlas.ti software. Next, the researcher loaded codes highlighted in Table 3.4 under code manager. The data categories and codes used to assess the results in this study followed a predefined analytical framework drawn from prevailing theories. Relevant code was assigned to a quotation and a brief comment inserted where necessary. The process was repeated for each document as illustrated in Figure 5.1 below. A report was then extracted based on the codes used. A sample of the report is shown under Appendix V.

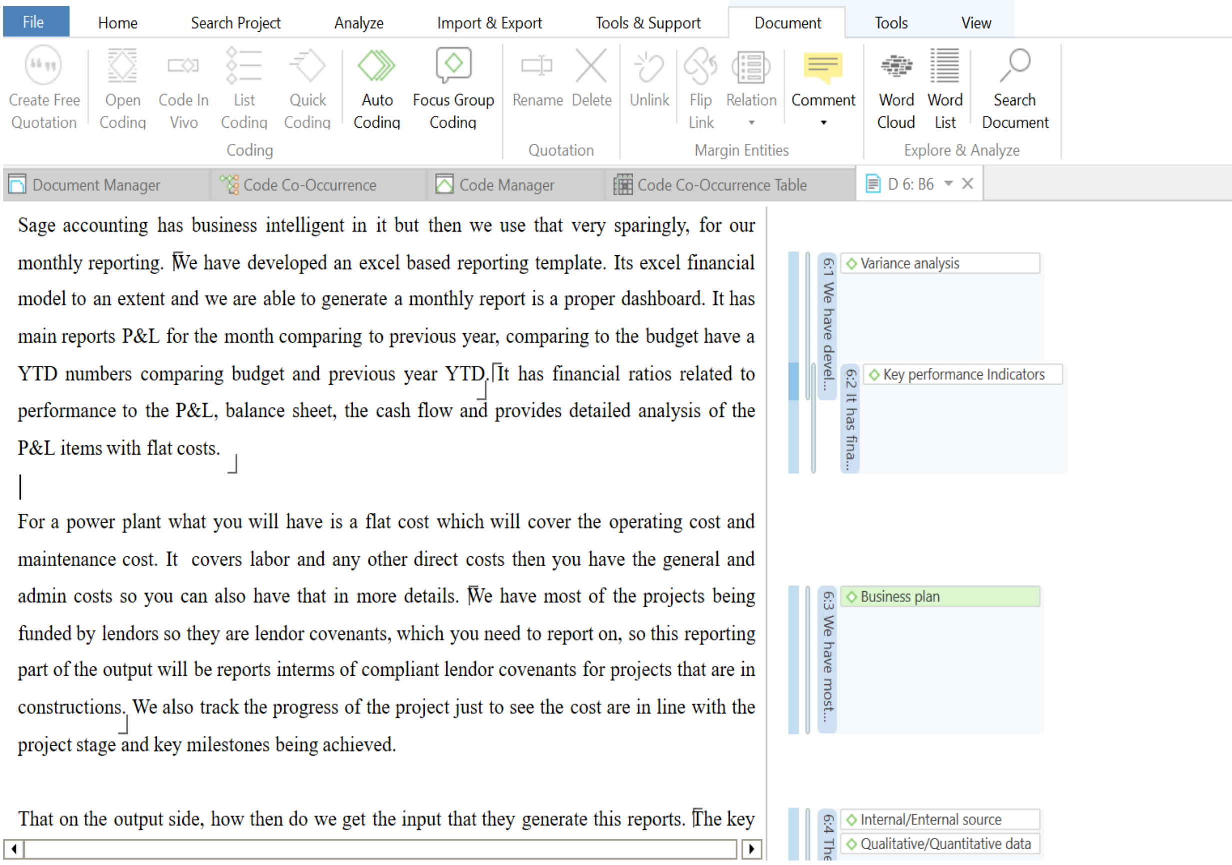

Figure 5. 3 Sample Interview coding using Atlas.ti

5.4 Qualitative Analysis

The research results were structured around the Four major themes identified in the initial conceptual framework (section 2.8), namely, Business intelligence capability (comprising technical, human capital and organizational dimension), organizational capability, complementary recourses and firm performance. Figure 5.2 provides a diagram of themes discussed in subsequent sections.

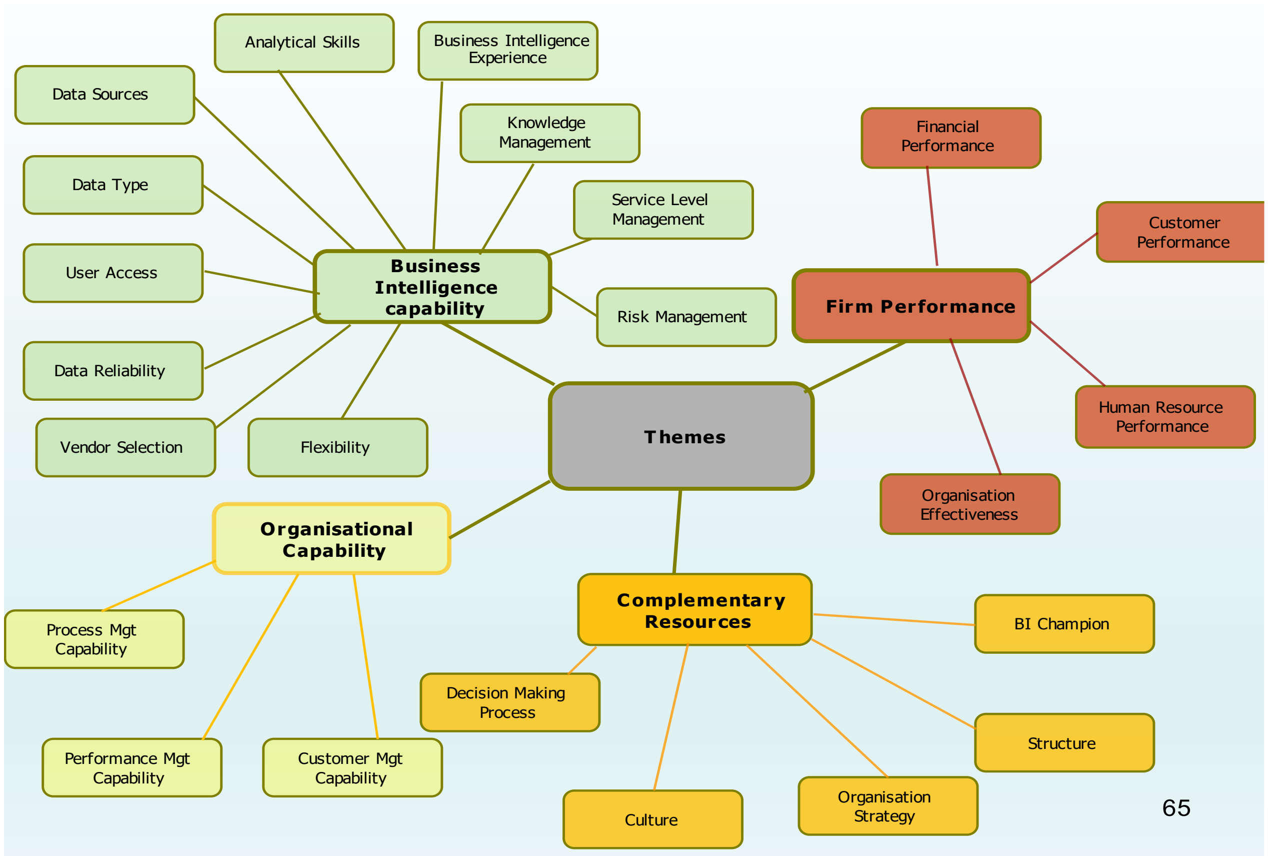

Figure 5. 4 Diagrammatical view of themes

5.4.1 Technical Dimension

In analysing BI capability, five sub-themes under technical dimension had been identified premised on an analysis of relevant literature and presented in a prior conceptual framework in section 2.8. Identified themes include data sources, data type, user access, data reliability and interaction capability. The interview focused on these five sub-themes and the findings are presented below.

Data sources quality. BI can load data from both external and internal sources (Negash, 2004). Internal data is ideally sourced from traditional application systems relating to processes, products, employees and performance. External data is produced during communication with clients, and suppliers and is rarely stored in a data warehouse. Shollo and Kautz (2010) underscored the importance of external data on the political, economic, social and technological dimensions. Organizations that source data from internal and external data sources have a broader range of data analysis possibilities. External data enables organisation to better understand customer base and the competitive environment. Schatsky, Camhi and Muraskin (2019) ascertained that external data sources enables businesses to tailor marketing packages, enhance HR decisions, achieve new revenue streams by launching new products or services, increase risk awareness and management, and better predict demand trends for their products and services. Multiple data sources, however, can lead to data quality issues, especially when the sources are external. Majority of participants concurred that data is sourced internally and externally, and systematic checkpoints are in place to ensure quality from these sources is good. Abstracts from B3, B7, B5 and B2 reflect this:

> *"We are capturing data from internal systems and external sources. For example, from Kenya Power and Lighting Company and Nairobi City Water and Sewage Company."* **(B2)**

> *"You are able to pull data from excel, from flat files, text files, Microsoft, Oracle, IBM and from PP2 in multiple formats. It can pull from internal and external sources".* **(B7)**

Interviewees B5 and B3 averred;

> *"Therefore, you have to put systemic checkpoints across the processes in order to make sure that the data quality is good."* **(B5)**

> *"Data is gotten from the team because everyone inputs his or her own data so from my end the only thing I will do is to verify and confirm that the data is valid"***. (B3)**

In addition, participants also suggested the need to have quality standards to evaluate the quality of data from identified sources. Variety of studies have shown that data from third parties can be swamped by inaccuracies (Schatsky et al., 2019). Excerpts from B7 asserts:

*"There must be some standard means of measuring quality. So, it means then that if you have 2 data sources and you want to mine data from both, if one source does not have the minimum data fields, it is a challenge."***(B7)**

Data type quality. Data type refers to the capability of BI to capture structured and semi-structured data. BI has historically been heavily dependent on structured data (Isık et al., 2013). Yet, countless sources comprise semi-structured data, such as web pages with competitor details, emails, sales force documents, and research paper collections (Baars & Kemper, 2008). Semi-structured data can provide more insight. For example, Lang, Ortiz and Abraham (2009) stated that output from this type of data can boost quality of early warning in the business. Internal complaint reports, customer email or call center records can provide valid intelligent feedback about emerging product challenges. However, inherent challenges in handing such data, for instance, misspellings and acronyms, must be tackled to ensure quality output. Whereas all participants agreed the application is able to capture quantitative and qualitative data, it is dependent upon the BI tool in use. For lower end tools like excel, what is captured is a brief commentary on the reports, Interviewee B3, B6 and B8 remarked;

*"Yes, it can access any format of standard data base or flat file irrespective of the location as long as you have the rights to access the data source". **(B3)***

*"Which makes it easier for them to compare since the reports are very detailed commentaries in terms of performance, the milestones being attained and the social impact of the project". **(B6)***

"It is mostly quantitative. Quantitative in terms of the numbers and qualitative in terms of customer description and their comments" **(B8)**

User access. This capability refers to the extent to which a user has access to BI. Although some organisations adopt BI systems that provide unrestricted access to data and reporting toolkits to all stakeholders, others provide relatively limited access (Havenstein, 2006). BI tools serve a specific purpose due to varying capabilities. Isik et al. (2013) suggest, considering organisations have various user groups, it is imperative to have distinct methods of access. Watson and Wixom (2007) asserts that user should be given data access tools that are relavant to their requirements. Participants stated they have adequate access and that rights are granted depending on the tasks to be carried out. This was demonstrated by excerpts from interviewees B3, B2, and B8.

> "*Access is given in reference to the level of hierarchy. At the lower levels, you are given access to your own information and opportunities relating to your customer. As you go up the hierarchy, for example, and you are the team leader, you have wide access to the data relating to your team".* **(B3)**

> "*The system is accessible. For instance, the sales team, who are the main users of the application are the ones who have the access icon. They have user rights, which determine to what extent they access the system".* **(B8)**

Interview B2 clarified that;

> "*Not everyone has access to the application. Rights are granted depending on the tasks to be carried out"*. **(B2)**

Some interviewees recommended appropriate steps should be taken to protect data from unauthorized access due to legal implications. The proliferation and widespread use of BI come with a range of security and privacy risks that must be resolved. Sherwood (2017) insists that the mere act of generating, receiving, or storing data is always a threat if it stays unsecured. Because BI insights are extremely valuable to hackers, it is particularly vital to secure data once the system has been deployed. When data is not secured, there is a great deal of danger of unauthorised access. Data should be encrypted at the very base level to prevent hackers from accessing it. An interviewee B5 remarked;

"Data privacy infringement rights will start bringing security issues to companies it's a whole field of study in itself and I can tell you in this country, yes we are getting it right to an extent, but there's a lot to be done". **(B5)**

Data reliability. It refers to the dependability of data to be processed for decision-making (Isik et al., 2011). BI helps organizations to collect and store a substantial volume of data. However, as data increases, it becomes increasingly complex to handle and hence, increasing the risk of poor data quality.

Reliability can be a significant issue when collecting data from external sources if proper control systems are not in place. Empirical evidence shows that unreliable data impacts organizations adversely (Graham, 2008). According to Loshin (2012), reliability can be assessed through completeness, currency, accuracy and consistency of the data at hand. Completeness test if a data set has all required records while accuracy relates to the absence of errors. Erroneous values can expose business to adverse impacts such as lost revenue generation opportunities. Currency reflects on how the examined data sets are up to date. Consistency takes into account the extent to which information can be corroborated in other available data sets. Interviewees stated the reliability is good and steps are taken to minimize errors. For example, by locking cells (B6), providing friendly interface (B5) and preventing data deletion (B3).

> "*So, deleting is not allowed even if you have put the wrong date so that the integrity to the data is upheld". * **(B3)**
>
> *"Yes, we do what we try to do is lock some cells to minimize input errors".* **(B6)**
>
> *"For data reliability, we measure it from generation to conversion to ensure it is complete and accurate".* **(B8)**
>
> *"The only time where you might need to make an adjustment to the report is when creating account that was not in the template. But this is centrally controlled, and the user has to inform the group and relevant people who will then assist in making that adjustment".* **(B6)**
>
> *"Reliability of the data is good. The process of that data input must have specific controls and measures".* **(B5)**

Interaction capability. This capability involves linking different systems and their data or software, whether physically or functionally, to generate more value beyond what each system provides. To ensure BI accurate outcomes, the degree and quality of interconnection between other systems and BI and other systems is paramount, specifically for organisation that collect data for multiple sources. Organizations must find ways of managing BI integration efficiently with other information systems (Shollo & Kautz, 2010). Participants observed that value was generated from BI tools when they are integrated to other systems. Interviewee B2, B7 and B6 reported;

> *"When we integrated with Ministry of lands and we began doing the business intelligence, our performance spiked immediately".* **(B2)**

> *"Now the other thing it is the same template or the same reports is used by the entire business in Asia and also in Africa and we have integrated 50+ projects".* **(B6)**

Interviewee B7 adds;

> *"We were looking for a tool that can access multiple data sources".* **(B7)**

Vendor selection. Interviewees cautioned the use of BI tool from the same vendor who has supplied ERP. The vendors are sometimes biased towards working with their product hence, limiting interaction with other systems due to high integration costs. Vendor assessment can be a challenge because almost all vendors try to attract clients with innovative features and sometimes pledge to come up with better stuff in future. Schiff and Michaels (2007) observed that perhaps more important than any particular feature or function is the credibility and long-term viability of the vendor. The authors recommend that selected vendor should be a market leader able to offer a wide range of integrated services, with great features and functionality to satisfy the current and well-defined future needs. The vendor should have a reputation for upholding their commitments, constantly reinvesting in products through upgrades, and a long-term probability of being around to offer support. Therefore, vendor selection is a critical dimension. Interviewee B7, for example, stated;

> *"Vendor selling a database tool would be biased to their tool working with their product for obvious reasons. You find, for instance, if Microsoft or oracle were selling a business intelligence tool, it would be primarily focused on their own proprietary databases. Now, most of them will tell you that it can work with all other systems, as they heavily market their own products. However, they'll place some punitive customization costs to slow integration process".* **(B7)**

> *"Initially, top management was unhappy because the standard reports from BI solution varied greatly from normal management reports. However, the supplier was able to customise to capture all relevant indicators".* **(B1)**

Interviewee B4 observed;

> *"We have succeeded because the BI provider we selected has given us support through regular training. When a new feature is added, the vendor conducts training for the team. We have also seen some of our proposals included in the new version. We are happy with the current vendor* **(B4)**

In summary, as depicted in Table 5.2, several factors have an impact on BI capability and include data sources quality, data type quality, user access and integration. Particularly data reliability is a critical dimension of BI capability. Erroneous values can expose business to adverse impacts. However, participants added vendor selection as an additional factor that affects value realization from BI. The vendor should be a market leader who is able to offer support and a wide range of integrated services.

Table 5.2 Technical Dimension key Findings

Theme/Dimension	**Description**	**Findings**
Business Intelligence (*Technical dimension*)	Technical dimension is reflected by • Data sources, • Data type, • User access, • Data reliability and • Interaction capability • Vendor selection*****	• Data is sourced internally and externally and controls exist to ensure quality from these sources is good. • Application is able to capture quantitative. However, for qualitative data it is subject to BI tool in use, • Adequate access rights are granted depending on the tasks to be carried out. • Need to protect data from unauthorized access due to legal implications. • Reliability can be a concern when collecting data from external sources if proper control system is not in place. • Value from BI is enhanced when integrated to other systems. • vendor selection emerged as an addition critical factor under technical dimension. Vendor should be a market leader able to offer support and wide range of integrated services.

**Additional factor that emerged from data analysis*

5.4.2 Human Capital Dimension

Analytical skills and BI experience were sub-themes identified under human capital dimension based on literature review.

Analytical skills. Yeoh and Koronios (2010) posit that certain skills required by the BI team, such as robust problem-solving abilities, a solid statistical foundation, coding competences, and domain understanding, are essential in enabling data-driven organization through effective BI use. The project team usually has to deal with a variety of platforms, different interfaces, connections to legacy systems and multiple tools. All these tasks necessitate a diverse set of competencies and skills. Therefore, a well-balanced combination of business and technical knowledge, is an essential capability (Yeoh & Koronios, 2010; Fink et al., 2017). Wiston and Wixom (2007) argued that users can be equipped with relevant skills through training. Interviewees B7, B8 and B5 associated the value generated from BI to the level of skills available in the organisation. In addition, adequate training is roll out to ensure users are equipped with relevant skills to use the application. The following quotes exemplify this observation.

> *"The quality of data is as good as the people in putting the data and the people will be as good as the level of training".* **(B5)**

> *"If you look at it generally, it is the sales team that uses it, and you can conclude that all of them must be knowledgeable and have relevant skills".* **(B8)**

> *"The vendors will tell you our products are better, but I will tell you for a fact nearly all BI tools in the market can derive benefits with appropriate training"* **(B7)**

BI experience. Fraiha (2011) indicated that employee's diversity and knowledge are factors influencing IT business values. Diversity manifests through variation in age, education, gender, nationality and other characteristics. This brings forth the need to share BI experiences because it takes time to acquire. Experience is a key source of knowledge. Interviewee B8 pointed out that experience is required to exploit BI tools in the organisation, but it is accumulated over a period of time.

> *"Relating experience, it's all about how often we use it in daily work activities. It takes you not less than five months to be experienced on what it does".* **(B8)**

Interview B5 observed that experience is also gained by benchmarking with other organisation that have realized value from BI deployment. Benchmarking is the process of assessing business processes and performance metrics against industry standards. The feedback can then be used to identify weakness in the deployed systems with a view of enhancing its use with inherent benefit of increasing competitive advantage. Below is an excerpt from participant B5.

> *"Best practices are borrowed from external markets and markets that have been able to experience this in a longer time than us".* **(B5)**

Knowledge Management. Interviewees also pointed out the need to develop Knowledge Management (KM) systems in the organisation to harness the BI skills and manage generated knowledge. Herschel & Jones (2005) defines knowledge management as the mechanism by which knowledge is collected, distributed and used effectively in the organisation. BI enables organisations to integrate data, unlock data, and convert information to knowledge, thereby empowering employees to make better and faster decisions. Hence, BI main focus is explicitly knowledge. On the contrary, KM deals with the creation of new knowledge and the dispersal of existing knowledge throughout the organisation. Thus, KM focus is on tacit and explicitly knowledge. By exploiting new knowledge generated from BI in the organisation, KM could influence the very essence of BI (Herschel & Jones, 2005). For example, B2 and B1 stated;

> *"In fact, what we have done, we have come up with a knowledge base whereby if you do it successfully, you just document it in the knowledge base, people will continue using it under those documented dimensions".* **(B2)**

> *"We have an intranet in the organisation where employees are encouraged to frequently share new knowledge gained and it is available to all staff. We also have a reward scheme for the best and valuable knowledge shared".* **(B1)**

Interviewee B8 observed;

> *"Cleaning and sort outing out data require higher skill and its normally a function of a senior back office support team, but I think we need a platform to share this capability".* **(B8)**

Drawing from the interviewee's feedback, it is apparent analytical skills and BI experience are important factors that have an impact on BI capability. However, the need to harness these resources through knowledge management and benchmarking is critical in sustaining competitive advantage. Skills and experience acquisition is expensive and it accumulated over a long period of time. Table 5.3 present summary findings under human capital dimension.

Table 5.3 Human Capital Dimension key Findings

Dimension/Factor	**Description**	**Findings**
Business Intelligence (*Human capital dimension*)	This dimension is reflected by • Analytical skills • BI experience • Knowledge management*	• Adequate training is rolled out to ensure users are equipped with relevant skills to use the application • The need to develop knowledge database in the organisation to harness the BI skills emerged. • BI experience is required to exploit BI tools in the organisation, but it is accumulated over a period of time, hence the need to manage generated knowledge.

**Additional factor derived from data analysis*

5.4.3 Organisational Dimension

Two factors were identified from literature review under the sub-theme, organisational dimension. The factors include flexibility and risk management**.**

Flexibility. It refers to the capability of BI to provide decision support when variation exist in business process, technology or business environment. Participants remarked that the application they use is flexible in terms of access levels and scalability in relation to storage and integration to other systems. According to Yeoh and Koronios (2010), application selected should have scalable capabilities to include more data sources, attributes and dimensional areas of fact-based analysis. Furthermore, it should also incorporate increasing data from vendors, regulatory agencies and industrial trademarks.

The following segments from interviewees B7, B6 and B8 reflect this;

> *"Yes, it's quite flexible. That's the reason we went for it. From our experience, we found that a vendor selling a business intelligence tool and the same vendor still selling a database tool would be biased to their tool working with their product".* **(B7)**

"Whichever format is acceptable. It does not have to be that cash has to be on top and bottom. You can even have other expenses mixed up". **(B6)**

"Systems IS flexible and easily scalable". **(B8)**

Service level agreement. The interviewees brought forth the importance of having a dedicated development team to support any changes to the application. The need for service level agreement (SLA) was also highlighted by participants. SLA describes the level of service expected from a vendor, the benchmarks by which service is assessed, as well as the remedies or penalties if agreed service levels are not achieved. As mentioned by Overby, Greiner and Paul (2017), SLA protects all players to the agreement and hence, should cover the elements of services and management. Service elements should comprehensively cover specific services provided, service availability levels, obligations of each party, guidelines for escalation and costs relating to annual support. According to Overby et al. (2017), the management component should include the description of measurement criteria, reporting processes, scope and frequency, conflict resolution and mechanisms for subsequently updating the SLA. Yeoh and Koronios (2010) espouse that ambiguous and uncertain service-level contract with vendors is one of the major hiccups towards realisation of value for BI. For instance, interviewees B5, B7 and B2 stated that;

"Obviously when you are subscribing to a system currently as it is, it is always important that you get a development team backing up that particular piece of development. SLA with a vendor should be noticeably clear on the issues such as upgrades and timelines". **(B5)**

"They have API's for all major formats and standards and it's a key selling point. *We ensured this requirement is covered under the agreement we signed".* **(B7)**

"Perhaps one of the key success factors was the service level agreement with a vendor. For example, it is crystal clear from the agreement on response time.... *we measure monthly and surcharge against annual maintenance fee".***B2**

Risk management support. It refers to BI capability to support decisions associated with a high level of risk. Staff, technology, procedures and even external forces can put an organization at risk. BI can assist organisations in managing risk by tracking the organization's financial and operational performance and controlling the organisation's operations through key performance indicators (KPIs), alerts and dashboards (Yeoh & Koronios, 2010).

Interviewees agreed that BI support business planning by providing the analytical capability to spot opportunities, performance monitoring and forecasting. The following extracts from interviewees B3, B5 and B8 reflect this;

> *"It is only used for business planning whereby we are able to know that probably we expect such opportunities from earmarked customers".* **(B3)**

> *"The output is used to monitor the key performance indicators".* **(B5)**

> *"Risk management initiatives are in place, aided by BI tools…. once a customer has been brought in from a risk rating, you can determine the likelihood of defaulting using this tool, hence, give the customer a higher risk factor".* **(B8)**

Furthermore, interviewees remarked that BI provides insight to top management in the strategic decisions making process that is naturally associated with risk. This was reflected in extracted remarks from interviewees B7 and B5;

> *"So, for us the end goal is giving actionable insight to the leadership and more as a strategic or leadership tool than an operational tool".* **(B7)**

> *"It informs me that I have a market that has emerged, and I need to go there and identify what's happening".* **(B5)**

In addition, participants emphasized that BI tools support pricing decisions geared towards mitigating business risk. An extract from interviewee B7 highlights this;

"The beauty of it is that you are able, based on the trend to run a report in the future, for example, when you put in a pricing risk of a loss ratio of 5% based on the average, you can determine what it means in terms of profitability". **(B7)**

In summary, as presented in Table 5.4, flexibility and risk management provides desired capabilities under organisation dimension. However, it is vital to have a development team that support required changes to the application. The need for SLA with vendors emerged. Ambiguous SLA is a major hiccup in realisation of value form BI. The tool also provides analytical capabilities in strategic and pricing decision making process geared towards mitigating business and credit risk.

Table 5.4 Organisational Dimension key Findings

Dimension/Factor	**Description**	**Findings**
Business Intelligence (*Organisational dimension)*	Organisation dimension Reflected by • Risk management and • Flexibility of BI tool • Service level agreement*	• Application in use is flexible in terms of access levels and scalable in relation to storage and integration to other systems. • Importance of having a dedicated development team to support any changes to the application was highlighted. • BI support business planning by providing analytical capability to spot opportunities, performance monitoring and forecasting • BI provides insight to top management in strategic decisions making process that naturally is associated with risk. • Service level agreement is a critical capability in accelerating value from BI. Timelines, penalties and upgrade schedule should be defined.

**Additional factor derived from data analysis*

5.4.4 Organisational Capability

The next global theme was organisational capability. As summarized in the reviewed literature, it was mirrored by process, performance, and customer management capabilities.

Customer management capability. It is the ability to generate and sustain customer relationships. It demonstrates the quality of relationship an organisation has with customers and how well it is able to gain, satisfy and keep these customers. Liang and Tanniru (2006) observed that in the current business environment, customers expect a quick response to their evolving needs. Effective BI capabilities allow the organisation to obtain customer information by enabling deeper analysis of data (Audzeyeva & Hudson, 2016). Customer profiles can be analysed to define their expectations in terms of services and products. BI tools enables the user to drill down customer service data and evaluate the feedback for appropriate action. For example, the technology support different communication channels with customers, including e-mail, internet, mobile, twitter and other social medial channels. Karimi et al. (2001) concluded that organisations with a greater ability to plan and manage their IT resources and as well as provide timely, accurate and reliable data to relevant parties are more effective in enhancing service to customers.

Majority of the interviewees agreed output from BI is used to manage customer expectations and predict preference. For instance, interviewees B3, B2 and B8 stated;

> *"We are able to know the probably of expecting additional sales opportunities from such and such customers".* **(B3)**

> *"We are able to do the predictive analytics whereby if you come and want service X and we realize it's the service you access every month, then we ask you in advance whether you want that service".* **(B2)**

> *"It can also create a customer service report that covers the whole activity experience with the customers".* **(B8)**

Interviewee B5 and B8 acknowledged that BI support customer service level agreement management. SLA with customers describes the level of service expected by the client, the benchmarks by which service is assessed, as well as the remedies or penalties if agreed service levels are not achieved. BI tools permit management to measure satisfaction rates and delivery times quickly and easily based on collected data. For instance, the user can determine how quickly orders are fulfilled and whether deliveries are made on time. The information can then be evaluated, strategies designed and implemented to improve customer satisfaction. Habul, Pilav-Velić and Kremić (2012) argued that BI applications and solutions facilitates progressive customer relationship management, which is a foundation of an effective customer intimacy strategy. It means that every customer gets exactly what they want and when they want it. Below are remarks extracted from interviewees B5 and B8.

> *"That every time a customer goes into the system, they are able to see that yesterday we picked 100 pieces and determine how many items were delivered by 9 o'clock and 10 o'clock as stipulated".* **(B5)**

> *"Also, we use it in scheduling customers' requirements. So, if a customer wants to receive the service at certain intervals and preferred mode of delivery, the details are captured".* **(B8)**

Process management. It refers to the capacity to effectively steer firm's activities. Organisation takes a number of processes to achieve its strategic goals, providing multiple opportunities for IT implementation to streamline business operations (Melville et al., 2004). BI facilitates generation of customer financial or supplier-related real-time operational data from different sources such as point-of-sale databases, the internet, intranets, manufacturing facilities, third parties and other external sources. BI output thus provides the right insights for organisational tactical, and strategic decisions. Melville et al. (2004) assets that IT systems capabilities facilitate faster and more adaptive processes modification in response to business environment changes, which in turn increases organisational efficiency. Majority of interviewees strongly indicated that BI is used to monitor processes in the organisation. For instance, this was clearly reflected by interviewees B5 and B8.

> *"Hence, I'm able to put control measures in place, then check the deviations. Where there is a deviation on delivery time, it will flag an alert that is a service violation. That also triggers an internal improvement action".* **(B5)**

> *"We are able to factor that in the business operations workflows and assign responsibilities and accountability. We can also determine how best the project can be delivered, and apportion funds ensure delivery within contracted terms".* **(B8)**

In addition, participants observed BI can trigger a change in the organisation process. BI enables management to gain smart insights into the current state of processes. It provides users with means to measure process execution and gain insight into future workflow design improvements. BI tools can map performance metrics in process modelling, such as throughput and flow rates. Actual execution is then measured and displayed in performance dashboards and reports in real time. Thus, corrective action is taken in the event of process degradation. The following responses extracted from interviewees B8 and B2 reflect this;

> *"We have stopped some processes like going out to customers as we do analytics and sent you a statement and tell you we know you owe us this much, but please come we talk".* **(B2)**

> *"We are also looking at scheduling activities with all required resources in order to perform a service better by using BI to monitor the execution of all our services".* **(B8)**

Performance management. The third sub-theme under organisational capabilities was performance management. It refers to the capacity to design and monitor business performance. According to Bogdana et al. (2009), BI support business performance by providing an environment that first, connects business data to operational data for a complete view of the organisation. Second, it provides an environment for implementation of business rules and key performance indicators so that business activities can be managed consistently. Third, instant generation of warnings to proactively manage problems rather than reactive approach to mitigate the impact. Finally, streaming of real-time data to facilitate business process monitoring through well designed dashboards. Empirical research by Richards et al. (2014) confirmed that BI has a positive influence on planning and analytical effectiveness. The authors noted that BI reports present historical data that guide objective setting for subsequent planning periods and tools to analyse data for better insight.

Interviewees agreed that BI is one-stop shop for all stakeholders in the organisation. BI output is used to evaluate performance to trigger corrective action to mitigate crisis. Interviewees B3, B5, B7 and B6 remarked;

> *"It is a one-stop shop for you at management level because it gives you all required information. You are able to see how your business is performing from your laptop or desktop".* **(B3)**

> *"Thus, BI gives you a real time methodology intelligence information to be able to man service expectation".* **(B5)**

> *"Exactly that's where we are going, into the point of exception reporting, monitoring of thresholds and the ability to pick out variances before we have a crisis".* **(B7)**

> *"Which makes it easier for them to compare since the reports are very detailed commentaries in terms of performance, milestones and the social impact of the project".* **(B6)**

Furthermore, participants observed that BI tool is actively used to manage staff performance. Lucero (2018) identified seven ways employee performance can be managed by BI. Applicable areas include recruitment, customer sight, communicating expectation, coach and mentoring, monitor performance engagement forum and reward for good work. BI output can be utilized to monitor employee performance against target. If some employees are continually underperforming, this should mean that you have to take action. For example, if any management support is required to improve or any lesson can be learned from staff who are performing better. Interviewee B3, for instance, remarked;

> *"The application is very good in managing staff performance. That's because targets for each staff are keyed into the system at the beginning of the year".* **(B3)**

Equally, interviewees mentioned that application is used in trend analysis by comparing results across selected period. BI enables the roll-up and drill-downs of key indicators examined for deeper insight (Bogdana et al., 2009), For example, interviewee B6 stated;

> *"We have developed an excel based reporting template. It has primary reports that are frequently used such profit and loss for the month, comparing to previous year and budget. We have a year to date numbers comparing budget and previous year".* **(B6)**

In summary, the findings are depicted in Table 5.5. BI output, support management of customer level agreement and forecast change in customer preferences. In addition, it is used to manage business processes and also triggers process changes. Furthermore, it enhances business performance by comparing actuals to target and conduct trend analysis thus enabling management to take corrective action to avert crisis. Finally, the tool also supports staff management in the organization.

Table 5.5 Organisational Management Capability Key Findings

Theme	**Description**	**Findings**
Organisational capability	The theme entails • Customer management, • Process management and • Performance management capabilities	• Output from BI is used to manage customer expectations, predict preference and manage service level agreements. • BI is used to monitor processes in the organisation • BI can trigger a change in the organisation process. • BI is one stop shop for all stakeholders in the organisation. It used to evaluate performance in order to flag corrective action to mitigate crisis.

5.4.5 Complementary Resources

Complementary resources are other assets that help to generate information technology related benefits. This covers decision-making process, culture, structure and organization strategy, as abstracted from the literature review.

Decision-making process. It is a process of making choices by identifying the problem, establishing alternative solutions and selecting the best option. Elbanna and Child (2007) observed that there three dimensions to a decision process that is political, intuition and rationality. Rationality reflects the extent to which decision making process includes collecting information related to the decision and relying on the interpretation of this information to make a choice between various alternatives. Under the political behavioural dimension, decisions arise from a process wherein decision-makers have diverse objectives, form alliances to achieve these goals, and the desire of the most powerful person is considered. Intuitive processes arise at unconscious and subconscious levels. Decisions are made based on gut feelings. BI is effective in rational decision making environment. Majority of those interviewed affirmed that the need for objective and fast decisions, has enhanced the use of BI in the organization. Extract from interviewees B3, B5 and B2 echoes this observation;

> *"Yes, the output for the application is 100% for decision making".* **(B3)**

> *"The output from this application basically for decision making across the business at all levels".* **(B2)**

> *"....so that accessibility of information allows decision making especially where there're exceptional cases. Hence, managers are able to address issues fast".* **(B5).**

Strategic decision-making requires the selection of options to support the path to the desired future. This process takes place at the top management level and involves determining strategic direction that may affect the business future growth and viability. However, Lieber (2016) noted this process is prone to considerable cognitive bias. The author observed BI, via its ability to distill knowledge from today's massive data flows, offers unique leverage points to support good strategic decision making and provides factual data-based sources to mitigate cognitive bias. Recent empirical study results by Aghaei (2013) indicate that when applied in strategic decision-making processes, business intelligence has significant positive impact on strategic decisions aspects such as efficiency, productivity, flexibility, agility and as well integration. Participants also highlighted that business leaders use BI to make strategic decisions. This was evidenced by excerpts from B5 and B7, who stated;

> *"As a business leader seeing that it almost tells me, either to increase my routing in this specific area or informs me that I have a market that has emerged and I need to go there and identify what's happening".* **(B5)**

> *"The output from the application is used in strategic making process".* **(B3)**

Culture. It refers to organisation, norms, values and beliefs that promote a healthy and favourable atmosphere, which contributes to the flow of information between different organisation groups. It seeks to make decisions quickly and accelerate performance benefits (Arefin et al., 2015). Organisation with strong and conducive culture, enhances staff ability to digest information from various sources for effective decision making and accept positive organisational changes. Ravasan and Savoji (2019) posit that implementation of BI systems necessitates some organisational changes. It is usually accompanied by the resistance of the employees when deploying the solution. Majority of those interviewed concerted that culture has an impact on how staff use the application. However, due to benefits associated with this tool, no resistance was encountered at the time of implementation. Watson and Wixom (2007) argue that utilization of information in decision-making should be part of the organisation culture in order for BI to realize value. For example, interviewees B3, B2 and B6 reflect this position;

> *"We have not really faced resistance in using the solution because we have users occasionally who need better systems".* **(B6)**

> *"Therefore, there is a change in processes. We have even stopped some processes and others; we have re-engineered them towards that line to make them more efficient. Our staff supported the project because benefits were highlighted".* **(B2)**

> *"Culture has an impact on how staff use the application".* **(B3)**

Interviewees observed that BI deployment is a journey and it is important for stakeholders across the business to take ownership. It is not an IT team project but business initiative. Excerpt from interviewee B7 and B2 demonstrate this position;

> *"Ownership at the highest level and across the business is vital in generating benefits from BI. All stakeholders must take ownership in their respective areas of operation".* **(B2)**

> *"I would say one of the things that I would want to highlight is that it's not a one-off thing, it's a journey…….It is important that leaders are aware that this is not a vendor or an IT driven initiative, it's a business initiative".* **(B7)**

Structure. The third sub-theme was the structure. It refers to the forms of authority, communication channels and nature of relationships in the organisation. According to Arefin et al. (2015), centralisation and decentralisation are common variables correlated with structure. The authors concluded that BI systems tend to be successful and have an impact on the performance in decentralised setup in which information is relayed to stakeholders without delay. The participants interviewed indicated that BI is more effective in a decentralised structure where ownership spans across the business but could not confirm it has impacted their BI rollout. Extracts from B7 and B8 support this argument.

> *"If you really want to exploit the BI, then you structure has to be flat".* **(B8)**

> *"The last one I would say is ownership at the highest levels and across the business is vital in generating benefits from BI".* **(B2)**

BI champions. Participants recommended the selection of BI champions in each section of the organisation. BI champion is an individual who has passion and the drive for this innovation and unreservedly helps others get the full benefits of this tool. Champions play a vital role in persuading employees to embrace organisation vision and adopt new technology. Wixom and Watson (2001) suggest that the champion should be closer to users' daily actions and goals. Similarly, Yeoh and Koronios (2010) suggested that BI champions should have excellent business acumen to enable them to envisage any organizational challenges and change course accordingly. By approaching BI systems from strategic and organizational viewpoints, the champions need to ensure coordination between business units and BI project team. For instance, interviewees B7, B1 and B4 remarked;

> *"Internally, you identify who owns the data, who is responsible for ensuring the quality of the data at departmental levels or functional levels. Hence, we have champions within each department who ensures the quality of the data is upheld".* **(B7)**

> *"We have champions from every department. They are super users who are trained, and they then are responsible for training users in their departments in addition to normal vendor trainings".* **(B4)**

> *"We have super users in all seven divisions to drive our BI agenda. They meet monthly to review the BI road map. For example, suggest and fast track enhancements".***B1.**

Organisation strategy. The final sub theme under complementary resources organisation strategy. It refers to plans of achieving organisational goals. The correlation between the strategy of the organization and the effectiveness of BI is clear. BI system provides information to enable top management to make strategic decisions that has an impact on performance. Bergeron et al. (2004) observed that firms that perform dismally have week alignment between IT and business strategy. Ravasan and Savoji (2019) stated that by aligning IT and business strategies, it contributes to IT growth and development in organizations and equally IT strategies lead to a change in business strategies. Yeoh and Koronios (2010) argues that management should also provide the necessary budget and financial resources for the adoption and implementation of BI systems. Interviewees agreed that BI value realisation is shaped by strategic direction of the organisation. Extracts from B3 and B7 suggest that BI falls along the critical path and hence, the need to exploit value from data.

*"Data is becoming the new strategic imperative. We have stepped into big data era………… as you know big data allows you to access data from internal and external sources. We are now able to get more valuable information to guide us in allocating resources".***(B7)**

"We are looking towards a data driven intelligence led decision maker, so you find that these analytics falls in the critical path towards that realization". **(B2)**

Respondents also noted that during the business planning process, management relies on BI output. Bolander (2019) argues that poor quality of data has far-reaching consequences. Such negative impacts include poor business strategies, greater financial loss, decreased productivity, a tarnished reputation, and wasted opportunities. Inaccurate decision-making on the basis of incorrect data results in multiple mistakes, inconveniences and also leads to higher costs. Gartner's research shows, on average, the annual cost to businesses due to poor data quality is about $9.7 million (Bolander, 2019). Therefore, data quality can affect the strategic direction of the organisation. Excerpts from interviewees B3 and B8 exemplified this observation.

"Management use that information to forecast. So, when they set up targets, they use the information from the system". **(B3)**

"More importantly, you are able to go back to history and compare……. and map the change to the external environment to forecast what the future will be like. It can also be used to address emerging issues in the business". **(B8)**

Likewise, participants indicated that support from top management is crucial in the utilization of BI. Based on the leadership style displayed, they may pressure all stakeholders to use the application. Users also tend to live up to management expectations and are more likely to tolerate a system that they consider has been endorsed by their organization's leadership. Moreover, Yeoh and Koronios (2010) contend that committed support for management has been widely recognized as the most important factor in implementing the BI system successfully. Implementation of a BI system is not simply a procurement of software and hardware; it is a complex undertaking requiring sufficient infrastructure and resources over a long period of time. Watson and Wixom (2007) further emphasized the importance of support from top management in availing required resources and insisting on the organization's use of information-based decision-making. In particular, interviewees B2, BI and B4 remarked;

> *"The acceptance is very high due to top management support and in fact, it is now our strategic direction so those who are not supporting it now have no alternative other than accepting it".* **(B2)**

> *"The last one I would say is ownership at the highest level…… is vital in generating benefits from BI".* **(B2)**

> *"Management allocates resource every year for training and any further customisation as per changes in user requirements".* **(B1)**

> *"We stopped using excel reports in our monthly trading reviews. Our managing director insisted that all managers must extract reports from BI personally and present. This initiative has accelerated the use of BI our organisation. Previously, managers used to doctor excel reports before presentation".* **(B4)**

Table 5.6 summarizes the key findings under organisational management capability. BI Champions emerged as an additional factor that further enhances benefits derived from BI roll-out. Champions play a vital role in persuading employees to embrace organisation vision and adopt new technology.

Table 5.6 Organizational Management Capability Key Findings

Theme	Description	Findings
Complementary resources	Complementary resources include • Decision making process, • Culture, • Structure	• The need for objective and fast decisions has enhances the use of BI in the organisation. • BI is used by business leaders in making strategic decisions. • Prevailing culture in the organisation impact how staff use the application.

	• Organization strategy • BI champions*	• BI is more effective in a decentralized setup in which information is relayed without delay. • BI deployment is a journey and it is paramount for management at the top to take ownership of the process. • BI champions drive business intelligence agenda across the organisation.

**Additional factor derived from data analysis*

5.4.6 Firm Performance Dimension

Sales growth, customer performance, human resources performance and organisation effectiveness were identified from literature review as sub-themes for firm performance.

Sales growth. The growth was reflected through revenue increase. Business intelligence software can be exploited to classify your customers based on the date, regularity, and significance of their purchases to ascertain who your ideal clients are. This kind of profile enables management to design marketing activities geared towards sustainable organic growth from existing customers. In addition, managers are able to understand and organize the sales pipeline with BI and thus empower the team to prioritize the time spent on each type of prospect based on the conversion's probability and value.

Majority of the interviewees agreed that BI has positively impacted revenue in their organisation. Excerpts from interviewees B3 and B2 reflect this position.

> *"BI has an impact on revenue performance. We are able to plan, project and pick out a customer you feel, either at a particular level, can be influenced to secure the business".* **(B3)**

> *"The impact on overall performance is huge. In fact, when we started doing this especially for the county governments, we were able to make a huge gain. When we integrated with lands and use business intelligence, our performance spiked immediately".* **(B2)**

Customer performance. Habul, Pilav-Velić and Kremić (2012) posit that BI enables personalised relationships with customers and thus provides a better understanding of their perceptions and expectation. BI facilitates the collection of data from diverse sources, both externally and internally, as well as unstructured and structured data. This ensures customers get what they want and within a specified period. Participants confirmed the utility of BI tools to evaluate historical and current data, capture emerging patterns and identify opportunities. For instance, interviewee B5 stated;

> "*Even without doing anything, even without sending a salesperson out there, the system tells me straight 3% up on revenue based on the input data. We are able to analysis the data, review the trends and plan accordingly to ensure we have the capacity to handle a spike in activity levels"*. **(B5)**

Human resources performance. Once employees feel recognized for their efforts, they feel they are part of the organisation. They become more productive and committed. According to Lucero (2018), BI systems can automatically identify positive behaviour for workers with badges or special names, while monitoring staff progress and achievements on a regular basis. By displaying KPIs on a large screen, it helps keep workers up to date about the company's position and may encourage them to keep on improving. In addition, the sense of achievement helps to increase staff morale. BI also significantly improves staff productivity. Barua, Mani and Mukherjee (2012) in their empirical study highlighted that a 10% growth in data usability boosts revenue per employee by 14.4%. Increasing data usability involves enhancing data presentation, the simplicity at which data can be manipulated or processed, and the degree to which data across multiple databases is consistent.

Participants acknowledged that implementation of BI has improved staff morale due to improved processes and access to valuable data that helps them achieve their targets in the organisation. For instance, B5 and B2 stated;

> *"Staff morale has improved. The system improves the way of doing things and the burden of proof. You can trace parcels across the chain and hold respective*

> *individual accountable for damage or loss. This system enables you to point a finger and say it's here we have a problem".* **(B5)**

> *"The staff morale is good. Now guys in domestic tax section want it like yesterday, because they have a target they want to meet and if we can give them anything that can help them achieve the stretched targets, they are willing".* **(B2)**

Furthermore, interviewees pointed out that BI has improved staff performance. Previous research found that by the end of 2018 around 6,400 companies with more than 100 employees would be using big data analytics (Straz, 2015). BI provides detailed information about each of the organisation's employee to the human resources team. Employees can use BI reports to evaluate their performance against set targets. Outcomes monitoring also provides an opportunity for top management to communicate early with disengaged workers, offering feedback or resources that may help improve morale and results. BI output can also be used to reward good performance. It also provides the quality and quantity of the work performed by the employee. Constructive bolstering of good behaviour enables both the employee and those around them to improve their performance. With tools such as employee satisfaction assessments, team evaluations, social media and exit/stay interviews, management can foresee (and therefore, prevent) employee turnover. For instance, Xerox was able to reduce its attrition rate at call centers by 20 percent with the use of big data analytics (Straz, 2015). Excerpts from interviewees B3 and B8 reflect this position.

> *"These dashboards are used to reward performers and reprimand poor performers. Rewarding outstanding staff performance encourages others to perform better. We use data also to manage staff turnover, for example, we can tell from exit interviews what is driving staff away".* **(B3)**

> *"You can also look into each person's pipeline and you will be able to direct activities and actions around managing the concerned staff".* **(B8)**

Organisation effectiveness. Improved data quality has an impact on both top and bottom lines (and thus profit). Barua et al. (2012) posit that ROE improves by 16% for a 10% improvement in data quality and sales mobility. According to (Barua et al., 2012), performance improvements result from better and timely decisions (which increases customer satisfaction, loyalty and therefore, revenue), as well as fewer mistakes and reworks, reduced working capital requisites and faster receivables (which reduces costs). Sales mobility allows the sales team to configure customized products efficiently and enhance value by providing timely information to customers on all aspects of a transaction. Winning companies such as Continental Airlines (currently trading as United Continental Airline, based in Huston), have seen investments in BI (£30 million) generate a 1000% return on investment (Anderson-Lehman et al., 2004). The airline saved over $500 million in six years through improved sales and cost savings in areas like marketing, loss prevention, sales forecasting and surveillance, and data center governance. Previous empirical research also confirmed BI impact on financial performance in areas such as profitability, return on investment and liquidity (Mithias et al., 2011; Elbashir et al., 2008; Brynjolfsson et al., 2011).

Majority of participants concerted that BI has significantly improved profitability in the organisation. This observation was reflected by interviewee B5 and B2 as indicated below.

> *"My gross margin has improved by using this solution by 4%".* **(B5)**

> *"The impact on overall performance is huge. In fact, when we started doing this especially for the county governments, we were able to make a huge gain".* **(B2**)

Interviewees specifically observed that the overall impact was attributed to efficiency improvement by using output from BI. For example, investment by Michigan State University's Advancement department in BI generated a $34,434 annual savings as a result of workers not having to spend hours on routine data analysis. The payback period for this investment was 2.1 years, with an annual return on investment of 55% (Durcevic, 2018). Accessibility to timely information results in taking corrective action. Interviewees B8, B5 and alluded to this fact.

"However, importantly it enables the organization to upper up internal work process, which saves time and money in terms of delivering the service". **(B8)**

"Secondly, if you figure out the activities of writing from one paper, filling documents, in addition to activity of scanning one item to the next, you increase efficiency and profitability by eliminating this manual activities". **(B5)**

"We have timely access to information for decision making information. There is no manual intervention to cause delays". **(B7)**

Summary findings under performance management construct are depicted in Table 5.7.

Table 5.7 Performance Dimension key Findings

Theme	**Description**	**Findings**
Firm performance	Firm performance entails • Sales growth, • Customer performance, • Human resources performance and • Organisation effectives	• BI has impacted positively sales in the organisation. • The application has led to an increase in customer base by enabling management to capture emerging patterns and identify opportunities. • BI has improved staff morale in the organisation and in managing staff productivity. • BI has significantly improved profitability in the organisation. • The overall impact is attributed to efficiency improvement by using output from BI.

5.5 Key Findings from Qualitative Study

The results of qualitative strand of this study are summarized in Table 5.8. The study results were organized in reference to the conceptual framework described in Chapter 2. Save for data type, the findings supported all the themes identified in the conceptual framework. However, new themes emerged from the data analysis and include vendor selection, service level agreements, knowledge management and BI champions. It was evident from the analysis that capturing of qualitative data is subject to the type of BI tool in use. For lower end tools like excel, what is captured is only limited commentary on the reports, implying that few firms on NSE have not fully exploited value generated from qualitative data. Moreover, while the framework depicts BI experience and skills as notable factors under human capital dimension, what emerged strongly from the data analysis was knowledge management (KM). Participants acknowledged that KM enables organisations to gain insight and understanding from their own experience, with subsequent impact on performance. Hence, BI experience and skills were consolidated under KM. Vendor selection was identified by participants as an additional factor that enhances BI capability under technical dimension. Vendor assessment can be a daunting task because vendors try to attract clients with innovative features and often promise better products in the future. Sadly, for many organisations, the application often does not fully reflect what was described in the vendor proposal after implementation. The vendor selected should be a market leader capable of providing a wide range of integrated services and functionality to meet current and well-defined future needs.

Service level agreement (SLA) was also outlined by participants under organisational dimension as a significant factor. SLA specifies the level of service required from a BI vendor, the benchmarks on which service is measured and penalties if agreed service levels are not achieved, to ensure a successful rollout. Ambiguity and uncertainty in service-level agreements with BI providers is a major setback in generating value from BI application. Finally, participants clearly articulated the role of BI champions under complementary resources. Champions play a vital role in persuading employees to embrace organisation vision and adopt new technology. They evangelize the use of BI in their respective sections by mentoring the users, coordinating and refining new requirements that demand attention from the vendors.

Table 5.8 Summary of Key Findings

Theme/ Dimension	Description	Findings	Reference
Business Intelligence (*Technical dimension)*	Technical dimension is reflected by data sources, data type, user access, data reliability and interaction capability	• Data is sourced internally and externally, and controls exist to ensure quality from these sources is good. • Adequate access rights are granted depending on the tasks to be carried out • Qualitative data collection is subject to BI tool in use, • Reliability is a concern when collecting data from external sources is proper control system is not in place. • Value from BI is enhanced when integrated to other systems. • vendor selection emerged as an additional critical factor under technical dimension	Section 5.4.1
Business Intelligence (*Human capital dimension*)	Reflected by analytical skills, BI experience and knowledge management *	• Adequate training is rolled out to ensure users are equipped with relevant skills to use the application • The need to develop a knowledge database in the organisation to harness the BI skills and experience emerged.	5.4.2
Organisational dimension	Reflected by Risk management, flexibility of BI tool and Service level agreements *	• Application they use is flexible in terms of access levels and scalable in relation to storage and integration to other systems. • It is vital to have a dedicated development team to support any changes to the application. • BI support business planning by providing the analytical capability to spot opportunities, performance monitoring and forecasting • Service level agreement is a critical capability in accelerating value from BI	5.4.3
Organisational capability	The variable entails customer management, process management and performance management capabilities	• Output from BI is used to manage customer expectation , predict preference and manage service level agreements • BI is used to monitor processes in the organization • BI can trigger a change in the organization process. • BI is one stop shop for all stakeholders in the organization. It used to evaluate performance in order to flag corrective action to mitigate crisis.	5.4.4
Complementary resources	Complementary resources include decision making process, culture, structure organization	• The need for objective, strategic and fast decisions has enhanced the use of BI in the organization. • Prevailing culture in the organization impact how staff use the application.	5.4.5

	strategy and BI champions *	• BI deployment is a journey, and it is important for top management to take ownership of the process. • BI champions drive business intelligence agenda across the organisation.	
Firm performance	Firm performance entails sales growth, customer performance, human resources performance and organisation effectives	• BI has impacted sales positively in the organisation • BI has led to increase an in customer base. • BI has improved staff morale in the organisation and in managing staff productivity • BI has significantly improved profitability in the organisation • The overall impact is attributed to efficiency improvement by using output from BI.	5.4.6

**Additional factor derived from data analysis in reference to the original framework in Figure 2.3*

5.6 Chapter Summary

Analysis of data and findings of individual interviews are presented. First, the participants' demographic profiles were highlighted. Second, in reference to the initial framework in section 2.8, qualitative data analysis and findings were discussed under each theme. Finally, the observations were referenced to existing literature to validate the findings.

It is evident from the findings that BI capability is reflected through technical, human capital and organisation dimension. Technical dimension incorporates data sources, data type, user access, data reliability and interaction capability. However, the type of data collected is subject to BI tool in use. Lower end BI tools such as spread sheets cannot adequately handle qualitative data. Vendor selection, service level agreements and knowledge management are critical factors that drive BI capability. A vendor should have a reputation of upholding their commitments and constantly reinvesting in their products though upgrades. The need to have a comprehensive SLA with vendors that clearly specify the obligation of each part and costs relating to annual support was highlighted. BI capability enables higher organisational capabilities that consist of customer, process and performance management capabilities, which in turn affects firm performance. The impact is moderated by complementary resources comprising structure, decision making process, culture and organisation strategy. To accelerate realization of value from BI, selection of BI champions in each selection was recommended. BI champions play a vital role in persuading employees to embrace organisation BI vision.

CHAPTER SIX

DISCUSSIONS AND A NEW FRAMEWORK

6.1 Introduction

The predominant purpose of this dissertation was to investigate the relationship between BI capability, organisational capability, complementary resources and firm performance. Concurrent mixed method that involves combining elements of qualitative and quantitative approaches was applied as discussed in chapter three. For the quantitative strand of this study, data was collected from listed firms at NSE between September and October 2019. For qualitative aspect of the study, data was collected from eight participants between August and September 2019. This section also addresses the findings of the study's quantitative and qualitative strands. The results were first independently produced and subsequently triangulated. Hence, the process of triangulation is discussed. A new framework is also presented based on the findings.

6.2 Triangulation of Research Results

Creswell and Clark (2007) suggest six forms of mixed method designs (section 3.3). The study adopts a triangulation design to obtain different but complementary data to best understand the impact of BI on performance. There are four variants designs to triangulation and include the convergence model, the data transformation model, the validating quantitative data model and the multilevel model. The researcher settled on the convergence model. Under this model, qualitative and quantitative data individually before combining the results during interpretation. (Creswell, 2014). This approach permits enrichment of findings in a single study (Creswell & Clark, 2011).

6.3 Discussions of the Findings

This section addresses the findings of hypothesis testing. The results of the hypothesis test are then correlated with the outcomes of the study's qualitative strand and further contrasted with the literature's empirical findings.

6.3.1 Direct effect of BI capability on firm performance

Based on the IS capability theory (Peppard & Ward, 2004), nine BI capabilities were identified and include data sources, data type, user access, data reliability, interaction, analytical skills, BI experience, flexibility and risk management (Isik et al., 2013). These capabilities are core measures of a firm's ability to effectively implement and use IT systems (Aydiner et al., 2019). **H_{01}** hypothesized that BI capability has no effect on firm’s performance. This hypothesis was tested as shown in section 4.7.2 and path coefficients results were $\beta = 0.353$, t-value = 4.964 and *P*-value = 0.000. The predictive power result was $R^2 = 0.261$. The results imply that BI capability can explain 26 percent of the variance in firm performance. The findings also indicate a positive relationship between BI capability and firm performance that is statistically significant.

This finding is consistent with previous quantitative empirical studies on BI impact on firm performance. Fink et al. (2017) study conducted in Israel on the process of BI value creation, concluded that impact is generated along the path of capabilities at operational and strategic levels. Seven out of nine indicators of BI capability were covered by the measures selected and include reliability, flexibility, interaction, quality of data source, user access, skills and knowledge. Positive impact was reported at the operational and strategic level on all indicators of firm performance comprising financial performance, customer performance, HR performance and organisational effectiveness. AL-Shubiri (2012) observed that BI has a positive impact in three different categories namely; innovation and learning ability, intellectual capital and finance. Amini et al. (2021) demonstrated BI's capability in the risk management significantly reduce the inaccurate estimates attributed to uncertainties in business. A study by Roodposhti and Mahmoodi (2012) established a robust correlation between economic values in firms with mature BI systems and their ROE/ROI. Bharadwaj (2000) viewed capabilities as a rent generating resource that is not easily imitated or substituted. Empirical research by Bharadwaj (2000) confirmed a direct impact to profit and other cost related measures. Results from a study conducted by Yiu et al., (2021) indicate that the use BI system increases profit and minimizes risk substantially. However, other authors such as Chae et al. (2014) and

Oliveira and Maçada (2017) have pointed out that capabilities no longer have a significant direct impact on firm results.

Qualitative results confirmed the existence of BI capabilities since all listed companies had rolled out BI tools. It was established that data is sourced internally and externally and controls exist to ensure data quality is good. Generally, structured data is captured, but depending on the tool in use, semi structured data is also collected. In addition, users have adequate access, depending on the task to be carried out. Adequate training is provided to ensure users are equipped with relevant skills to use the application. The participants also confirmed that the application they use is flexible in terms of access levels and scalability in relation to storage and integration to other systems. Furthermore, the tools provide insight to top management in strategic decision making process that is naturally associated with risk. BI impact on performance was confirmed in revenue growth, staff management and efficiency improvement. For instance, interviewees B5 and B8 stated:

> *"My gross margin has improved by using this solution by 4%".* **(B5)**
> *"You can also look into each person's pipeline and you will be able to direct activities and actions around management the concerned staff".* **(B8)**

The results were in line with other qualitative studies. For example, Eybers (2015) conducted qualitative research on the theoretical utility of BI. A direct link between BI implementation and organizational performance was confirmed by the study. This is evident by the positive impact on sales figures, management of risk and compliance.

Knowledge management emerged as an additional aspect of BI capability. While the initial framework depicted BI experience and skills as notable factors, what emerged strongly from the qualitative data analysis was knowledge management (KM). John (2009) posits that source of new knowledge in an organization encompasses the sharing of experience, technical skills, mental models, and other forms of tacit knowledge. Hence, BI experience and skills were consolidated under KM. In reference to KBV, knowledge is regarded as the most valuable resource and the ability to manage it (Gharakhani & Mousakhani, 2012) is the key driver of competitive advantage (King, 2009). Shanmugam et al. (2020) empirical study conducted in Sri Lanka confirmed that KM has a direct effect on performance. Revenue / market share and profitability increased considerably for firms that had implemented BI and harnessed KM. Outcomes from Gharakhani and Mousakhani (2012) study indicate that all three KM capabilities (acquisition of knowledge, sharing of knowledge and application of knowledge) have significantly positive effects on corporate performance.

Data type was not confirmed from both strands. It was operationalised to capture qualitative and quantitative data. This finding is also coherent with the literature. Previous study by Isık et al. (2013, suggests that qualitative data has no impact on BI success. BI has traditionally depended heavily on quantitative data (Sirin & Karacan, 2017) to make structured decisions that require accurate and precise information. However, for decisions that are unstructured and sophisticated in nature, qualitative data is required. Myriad sources of information contain qualitative data, such as web pages with information about competitors, reports from the sales force and repositories of research papers (Baars & Kemper, 2008). Gupta and Rathore (2013 pointed out that the bulk of the data of is unstructured and represents 80% of the data floating within the organization. In making decisions, comprehending and complying with regulatory requirements and performing other business functions, information contained in unstructured data play a crucial role. Shivalker (2019) reported that firms that have successfully collected and managed unstructured data, get a competitive advantage over other firms. In contrast to tidy and mainly numerical structured data, unstructured data is sometimes textual and thus messy (Muller et al., 2016). Furthermore, Shivalker (2019) observed that in the absence of appropriate tools, organisations hesitate from handling this type of data. Hence, that could explain why firms listed on NSE are not utilising this type of data in spite of inherent value.

The theory underpinning the results in H_{01} is the IS capability theory. IS Capability theory emphasises on the ability of the organisation to combine, integrate, review and reconfigure resources as the need arises to derive value from IT investment. Save for the data type, all capabilities depicted in the conceptual framework were validated based on qualitative and quantitative findings. The relationship between BI capabilities and firm performance was found to be positive and significant. These findings corroborate the premise of the IS capability theory.

6.3.2 Mediating Effects of Complementary Resources on the relationship between BI capability and Firm Performance.

Complementary resources consist of non-IT resources and wider organisational capabilities that help to realize value from IT investment and include culture, structure, and organisation strategy and decision making process. Null hypothesis two (**H_{02}**) indicated that complementary resources have no mediating effect on the relationship between BI capability and firm performance. The moderation test results were as follows; $\beta = 0.558$, *P*-value = 0.000, t-value = 3.600 and $R^2 = 0.458$. The highlighted findings empirically show that at the significance level of ($P < 0.05$ and $t > 1.96$) the mediating impact of complementary resources is positive and statistically significant. The magnitude of mediation was partial (VAF = 60%).

Previous quantitative studies done on information systems documented a positive effect between firm performance and organizational culture. For example, results from research conducted by Rayat and Kelidbari (2017) confirmed culture has a significant impact on the effectiveness of BI. Further more, the effectiveness of BI has a positive impact on organisational effectiveness. Fink et al. (2017) reported that business value of BI depends on the complementarity and compatibility with institutional routines through which learning generates new knowledge. Arefin et al. (2015) observed in a study conducted in Bangladesh that BI systems are more successful in stimulating performance when there is a decentralized structure and swift relay of information to and from top management. The connection between organisation strategy and BI effectiveness is apparent in previous studies (Rayat & Kelidbari, 2017). However, empirical research by Isik et al. (2013) further confirmed that decision environment does impact the relationship between BI success and capabilities. The authors concluded that it is crucial to use the right BI capabilities in the planned decision environment to allow an organisation to reap maximum benefit from BI investment.

The qualitative results of this study further confirmed the role of complementary resources. For example, participants posit that BI is effective in a rational decision making environment. The value of BI is negated in an environment where decisions are based on political interest or intuition. Recent empirical study results by Aghaei (2013) indicate that when applied in strategic decision-making processes, BI has significant positive effects on productivity, efficiency, agility and flexibility of a firm. Qualitative study by shollo (2013) provides clear evidence that the output of BI is not the only input that stakeholders use when making decisions. Instead, its use is discussed, shaped and continuously re-framed according to the needs and interests of the stakeholders, the characteristics of a given scenario, and inputs from other the decision-makers.

It was also evident from qualitative findings that culture has an impact on how staff use the application. Organisation with conducive culture, enhances staff ability to digest information from various sources and accept positive organisation changes. Buchana and Naicker (2014) reported actual use of BI is largely influenced by positive attitude of staff. Empirical study by Audzeyeva and Hudson (2016) confirmed BI impact is influenced by core beliefs and organisation structure. Watson and Wixom (2007) echoed the need to integrate information use in decision making as part of the organisational culture to gain value from BI. Participants also stated that BI value realization is shaped by strategic direction of the organisation. Management provides necessary financial resources in developing BI capabilities. This finding is consistent with other studies, for instance, a study by Bergeron et al. (2004) concluded that firms that perform dismally have poor alignment between business strategy and IT strategy.

BI champion was the additional complementary resource that emerged from qualitative data analysis. BI champion is an individual who has passion and the drive for this innovation and unreservedly helps others get the full benefits of this tool. Champions play a vital role in persuading employees to embrace organisation vision and adopt new technology. They are a major part of BI communities of interest inside each department and assist in fostering user excitement to use the application. Yeoh and Koronios (2010) maintained that the role of BI champion is essential to ensure that the organisational challenges occurring during BI deployment are handled carefully. Kulkarni et al. (2017) noted that user involvement though selected champions in BI systems, is greater and more robust compared to conventional IS projects. It includes participating in interpretation of user requirement, configuration, training and customisation. Bose and Luo (2011) connected the presence of a champion to the success of almost any successful venture, especially projects requiring further user training and attitude change. The study, therefore, confirms the results of previous studies (Puklavec et al., 2018; Bose & Luo, 2011).

Top management support demonstrates the degree to which company's senior management perceives developing BI capability to be strategically critical (Kulkarni et al., 2017). Extensive literature highlights the critical role of senior management to ensuring successful implementation of IS related projects (Dong, Neufeld & Higgins, 2009). Specifically, Kulkarni et al. (2017) observed that top management play a vital role of articulating the value of BI application across the organisation, issuing policy statement relating to BI use, bankrolling new BI proposals, recruiting and selection of analytically skilled work force, measuring BI outcomes and seeking facts that support decision taken by stakeholders. Empirical study by Dong et al. (2009) revealed that different supportive behaviour achieves different results in IS projects. Hence, the authors posit that top management must tailor their support actions in order to attain desired results. Moreover, Yeoh and Koronios (2010) contend that committed support from management (as an organisation strategy) has indeed been broadly recognized as the most important factor in implementing the BI system successfully.

IS capability theory postulates that the firms should continually develop competencies to leverage the technologies, information it possesses and knowledge acquired to produce specific and tangible value through the realization of organisational objectives. The findings confirmed a positive and significant impact on performance when complementary resources are exploited to develop required competencies to ensure appropriate use of technology. For example, embracing rationality in decision making process and harnessing a culture that encourages sharing of knowledge among staff. The study identifies and validates additional resources that firms listed on NSE leverage to enhance BI capability impact on performance. The resources include culture, decision making process, organisation strategy and BI champions.

6.3.3 Moderation Effects of Organisational Resources on the relationship between BI capability and Firm Performance.

Organisational capability was conceptualized, based on the extant literature review to include customer, process and performance management capabilities. The third null hypothesis (**H_{03}**) stated that organisational capability has no moderating effect on the relationship between BI capability and firm performance. Moderation assessment involved bootstrapping process to test for significance and the results were as follows; P-value = 0.021, R^2 value = 0.357 and t-value = 2,302. The findings empirically confirm at the significance level of ($P < 0.05$ and $t > 1.96$), the moderating impact of organisational capability is positive and statistically significant. Likewise, in their survey-based study, Elbashir et al. (2008) discovered BI conveys benefits through improved business processes (business partner relations, inside procedure proficiency, and client insight benefits). A study Yiu et al. (2021) confirmed that businesses improve their profitability and lower risks of bottom line variation after applying BI systems in processes. Empirical research by Ray et al. (2005) concluded that shared information facilitated by IT has substantial impact on the firm's capacity to gain more customer insights and related business processes with a final impact on business performance. A study conducted by Mithas et al. (2011) concluded that BI capability plays a critical role in developing organisational capabilities. Consequently, these capabilities have a favourable impact on financial, customer, human resource, and organisational effectiveness (measures of performance in firm). Moreover, the results showed that BI capability has a great impact on performance management, then process management and management of customers. Habul et al. (2012) argued that BI solution enables progressive customer relationship management, which is a foundation of an effective customer intimacy strategy.

Qualitative strand of the study confirmed the role of organisational capability in enhancing performance benefits from BI. Participants demonstrated that BI is a one-stop shop for all stakeholders in the organisation. It is applied in performance management by flagging out corrective action to mitigate crisis. This solution is also used to monitor critical processes and can trigger a change to improve efficiency. BI enhances customer management capability with final impact on performance. This application enables the organisations to obtain intelligent information relating to customers by enabling deeper analysis of data collected from multiple sources such as e-mail, the internet, mobile and twitter. Customer profiles are analysed to define expectation, predict preference and manage service level agreements.

In summary, the findings from qualitative and quantitative strands support the rejection of **H_{03}**. Organisation capability has a moderating effect on the relationship between BI capability and firm performance. These findings resonate with Organisational learning Theory (OLT) propositions. OLT asserts that a firm must continuously review its actions and processes that lead to the attainment of the set objectives. BI capability, for instance, enables listed firms to capture and analyse consumer data, allowing relevant stakeholders to gain a deeper understanding ("learn") on changes in consumers expectations and preferences. Corrective action is then taken to satisfy and retain identified customers.

6.3.4 The Combined Effects of BI Capability, Organisational Capability, Complementary Resources and Firm Performance.

The fourth null hypothesis (**H_{04}**) stated that BI capability, organisational capability and complementary resources have no combined effect on firm's performance. To test this hypothesis, R^2 value was assessed. Direct path between BI capability and firm performance yielded predictive power of (R^2) 0.290. Moderated effect generated predictive power (R^2) value of 0.357. When complementary resources (mediation) was added to the model, R^2 improved to 0.458. However, when all constructs were tested jointly, the model generated a high R^2 value of 0.503. This implies that the model can unravel 50% of variations in firm performance. In conclusion, the combined effect of BI capability, complementary resources and organizational capability is greater than that of the individual effect on firm performance. Hence, (**H_{04}**) was rejected.

Previous empirical BI related studies that expressly investigate the effect of BI and how other assets blend with BI to deliver superior returns are scarce and diverse (Chen, 2012; Richards et al., 2014). The findings from Mithas et al. (2011) confirmed IS capability that plays a significant part in the development of organisational capability. In turn, these capabilities favourably influence firm performance. AL-Shubiri (2012) observed that direct impact on decision-making process and indirect impact on performance. Study by Richards et al. (2014) established BI has a direct impact on the effectiveness of planning, assessment, and analytics, as well as an indirect impact on operation effectiveness hence, enabling organisation performance. However, Arefin et al. (2015) reported that BI has a positive impact on organisation effectiveness where there is a close match between BI systems and organisation strategy, structure, culture and process. According to Ida & Graeme (2015), BI capability contributes to firm performance in two pathways: directly by building a single version of truth in the organisation and indirectly through CRM. CRM team and processes consume the insights generated by BI.

Qualitative strand of the study confirmed the overall impact on sales growth, human resources performance and organisation effectiveness. Participants agreed that BI has impacted sales. With this solution, the users were able to classify your customers based on the date, regularity, and significance of their purchases to ascertain who your ideal clients are. Participants confirmed the utility of BI tools to evaluate historical and current data, capture emerging patterns and identify opportunities. Habul et al. (2012) posit that BI enables personalised relationships with customers and thus provides a better understanding of their perceptions and expectation. On staff management, participants acknowledged that implementation of BI has improved staff morale due to improved processes and access to valuable data that helps them achieve their targets in the organisation. Barua et al. (2012) in his empirical study, observed that a 10% growth in data usability boosts revenue per employee by 14.4%. Interviewees also concerted that BI has significantly improved profitability in the organisation. The impact was attributed to efficiency improvement by using output from BI. This finding is constant with other empirical studies. For example, investment by Michigan State University in BI generated annual savings of $34,434 due to time saved from manual data analyses (Durcevic, 2018).

6.4 Integrating Qualitative and Quantitative Findings

Integration phase commenced by quantitizing findings from qualitative strand. Quantitizing entails transformation of qualitative data into a quantitative form (Onwuegbuzie & Leech, 2004; Creswell & Clark, 2018). Teddlie and Tashakkori (2009) outlined that quantitizing may entail simply counting the frequency of themes or responses. Sandelowski (2001) content that themes can be expressed numerically in scores, scales or cluster and simple descriptive statistics to exemplify the resulting frequency counts. Fetters, Curry and Creswell (2013) specified that a researcher can code the qualitative data and then count the frequency of codes to assess significance of the findings. Maxwell (2010) further argues that the use of numbers for qualitative researchers is a valid and useful technique when used as a supplement to the overall research process. Blaxter (1983), for example, enumerated the number of cases, in sequence of prevalence, that 46 women provided on factors that cause diseases to 11 categories. The category of cancer was most prevalent, while ageing category was the least prevalent. Blaxter identified the conditions most frequently cited, and the numbers of women who identified them. Furthermore, Witcher et el. (2003) derived frequency of each theme from the respondent matrix and subsequently computed percentages to ascertain the preference rate for identified themes. The most prevalent theme was student-centeredness (cited by 58.9 % of the sample). This was followed by subject knowledge (44.1 %), while professionalism scored (40.8%). Other researchers such as Taylor and House (2010) used frequency tables to present thematic findings. Enumeration of themes by Kamau (2017), enabled the researcher to identify significant items that were finally merged with quantitative findings in the revised framework. Themes with a frequency score of 55.2% were considered significant in a qualitative study conducted by Minor et al. (2000). Onwuegbuzie et al (2007) reported 58.9% of the surveyed members generated one or more descriptors that characterized a student centred demeanor. The ratio delineated large effect size. In a sequential mixed method study by Patterson (2013) a final set of themes had to meet the condition of being embraced by three or more observations to be included in the quantitative strand. This translates to a minimum score of 33.3%. Hence, for qualitative strand of this study, dimensions were rated by enumerating the themes (Creswell & Clark, 2018) as displayed in Appendix IX. Any sub theme with a score lessen than 40% was dropped.

Integration of results was achieved through a joint display of quantitative and quantitative findings. Creswell and Clark (2018, p310) described integration as "*centerpiece of mixed method research*". Creswell and Clark (2018) also pointed out that integration is inadequately presented literature because researchers perceive mixed methods as an approach to gather and analysis qualitative data and quantitative. This non-integrative strategy doesn't reflect the real value of mixed methods because further insights occur when output from both strands is merged. However, a major challenge for researchers with mixed methods approaches concerns the degree of integration between qualitative and quantitative findings. Bryman's (2008) study of social science journal papers published between 1994 and 2003 using mixed methods found that less than 50 percent presented qualitative and quantitative results in parallel, and only 18 percent of the papers actually combined the two sets of findings. Integration is a point in a research process where quantitative and qualitative findings are merged. Several steps suggested by Creswell and Clark (2018) were followed in the integration process and include obtaining final results from the two strands, seeking for common themes/concepts across both sets of results, developing a joint display to present two results together to easy comparison and finally, comparison of the findings in order to assess whether they confirm or disconfirm. A joint display is a way of presenting results by aligning quantitative and qualitative data in a single table or graph. Creswell and Clark (2018, pg.319) further sates that "*researchers are incorporating joint displays into their mixed methods studies with increasing frequency, particularly those studies that use a convergent design".* Guetterman, Fetters and Creswell (2015) postulate that the findings should simultaneously be displayed side by side to enable the researcher gain deeper insight beyond the information extracted separately from quantitative and qualitative results.

Comparison between qualitative and quantitative findings are presented in Table 6.1 below. The significance of each factor is reflected by the number of asterisks. One asterisk (*) means that the factor is insufficiently significant and hence, dropped from the final model. Two stars (* *) signifies the factor is significant and was retained. By examining the outer loadings in the measurement model, the significance of each factor for quantitative strand was assessed. Measures with loadings below 6.0 were rated as insufficiently significant and dropped as depicted in Appendix VII. Data type, for instance, under BI capability construct, was dropped after all measures failed to achieve minimum thresholds of 6.0. In addition, under BI capability and complementary resources, the qualitative findings of the study uncovered some other dimension that affect the effectiveness of BI. The dimensions include vendor selection, service level agreement, knowledge management and BI champions. They are identified by three asterisks (***) in Table 6.1.

Table 6.1 Significant Dimensions emerging from Quantitative and Qualitative Studies

Factor	**Description from quantitative research**	**Description from qualitative research**
Technical Dimension	Data source quality** Data type quality* User access** Data reliability* Interaction capability**	Data source quality** Data type quality* User access** Data reliability** Interaction capability** Vendor selection ***
Human capital Dimension	Analytical skills * BI experience*	Analytical skills * BI experience* Knowledge Management***
Organisation Dimension	Flexibility* Risk management **	Flexibility** Risk management ** Service level agreements***
Organisational Capability	Customer management** Process management** Performance management**	Customer management** Process management** Performance management**

Complementary Resources	Decision making process** Culture** Structure**	Decision making process** Culture** Structure*
	Organisation strategy**	Organisation strategy** BI champions*** Top management support***
Firm Performance	Financial performance** Customer performance** HR performance** Organisation effectiveness**	Financial performance** Customer performance* HR performance** Organisation effectiveness**

6.5 A Revised Framework

After triangulating the findings from this study's qualitative and quantitative strands, Figure 6.1 below depicts the revised framework.

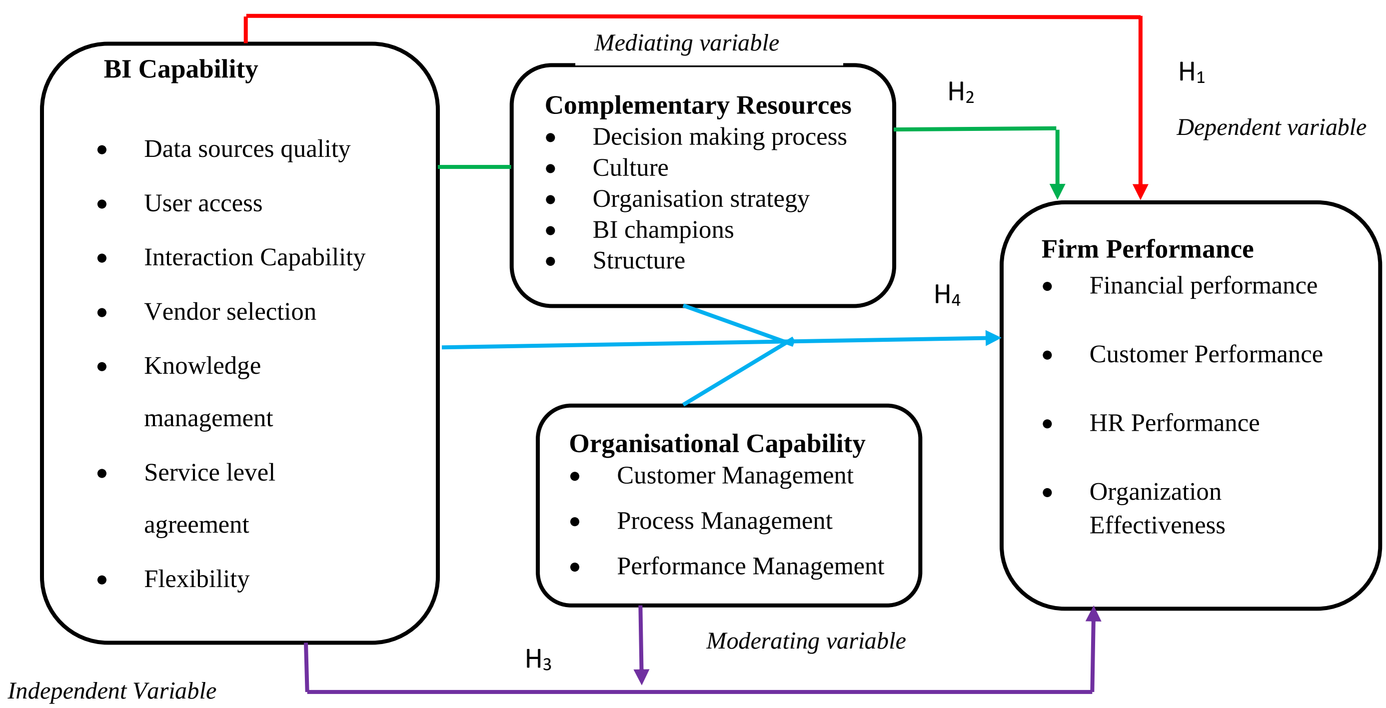

Figure 6.1 Revised Framework

Under the revised framework, BI capability comprises technical, human capital and organisation dimension. Technical dimension related factors include data sources quality, use access, interaction capability and vendor selection. Factors related to organisation dimension include service level agreement and risk management. Knowledge management is categorized under human capital dimension. Mediating variable, complementary resources comprises decision making process, culture, organisation strategy and BI champions. Organisation capability factors include customer, process and performance management. Firm performance entails financial performance, customer performance, human resources performance and organisation effectiveness. Tables 6.2 present indicators used in the framework.

Table 6.2 Final indicators in the Framework

Main Dimension	**Sub-dimension**	**Indicators**
BI Capability	Technical Dimension	Quality of data sources User access interaction capability Vendor selection
	Human Capital Dimension	Knowledge management
	Organisational Dimension	Service level agreements Risk management support
Organisational Management Capability	Customer management capability	Ability to determine requirements, expectation & preference of customers. Satisfaction and retention of customers. Customer database
	Process management capability	Reduced operation cost and improved efficiency of internal processes.
	Performance management capability	Ability to gather and monitor KPIs, ability to link metric analysis with decision making, feedback to stakeholder on performance
Complementary resources	BI champions	BI departmental user preventatives/ BI super users
	Culture	Shared values and beliefs that shape behavioural norms
	Decision making process	Political behaviour, Intuition and Rationality in decision making.
	Organisation strategy	Analysis, defensiveness, futurity and proactiveness

	Top management support	Articulation of BI value, investment in skilled talents, policy on use of BI, measurement of BI outcomes, seeking facts in decision making process
Firm performance	Financial performance (FP)	Sales growth- Increase in revenue, increase in profits and return on investments-Earning generated from invested capital
	Customer performance (CP)	Extent to which customer complaints have dropped and loyalty has improved. Growth in customer base.
	HR performance (HP)	Extent to which employee satisfied, developed, demonstrate exceptional performance and retention
	Organisational effectiveness (OE)	Demonstrated innovation, efficiency in work processes, cost reduction and improved coordination with partners

6.5 Chapter Summary

This chapter addressed data analysis results from qualitative and quantitative strands of the study. Convergence model under triangulation design was adopted. Data was collected separately but converged during interpretation. Quantitative findings indicated significant positive relationship between BI capability and performance. Mediating effect of complementary resources on the relationship between BI capability and performance was confirmed to be positive and significant. The results also confirmed the moderating effect of organisational capability. Furthermore, the combined effect of complementary resources, BI capability and organisational capability was confirmed to be higher than the individual effect. The findings from qualitative data were presented and discussed. These findings were also contrasted with previous studies on a similar topic. Finally, comparisons between qualitative and quantitative were presented and only significant factors were retained in the revised framework.

CHAPTER SEVEN

SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

7.1 Introduction

This chapter presents an overview of the research findings in relation to research objectives. It also discusses the conclusions from the results of the study, recommendations as well as contributions to theory and methodology. This chapter further addresses the research's limitations and proposes prospective gaps for subsequent research.

7.2 Summary of Findings

The overall objective of the study was to establish the impact of BI capabilities on performance of companies listed on the NSE. The following relationships were evaluated as shown in Figure 2.3; the relationship between BI capability and firm performance; the moderation impact of organizational capability and mediation effect of complementary resources on the association between BI capability and performance. The combined effect of BI capability, complementary resources and organisational capability on the overall firm performance was also examined. To fulfil the research objectives, factors listed in the research framework were identified in reference to information capability theory, knowledge-based theory, organisational learning theory and comprehensive literature review. The objective of the study was also met by employing mixed method research design. A survey was conducted for the quantitative thread of the study and data from 55 firms listed on the NSE out of a possible 63 companies was collected. Second generation tool (PLS-SEM) was used to analyse collected data. PLS SEM was suitable because of the limited number of businesses listed on the NSE and does not necessitate the distribution of data to be normal. The study used SmartPLS 3.2.1 software to analyse the data. For qualitative strand, data collected from eight respondents was coded and structured using Atlas.ti version 8. The results were triangulated at the interpretation phase.

The study was driven by four specific objectives that primarily assisted in crafting hypotheses for the quantitative strand of the research. The first objective was to establish the effect of BI capability (that comprises technological dimension, the human capital dimension and the organisational dimension) on performance. Based on the outcomes of both strands as illustrated in section 6, it was demonstrated that the technological dimension, the human capital dimension and the organization dimension have a significant and positive effect on firm performance. In reference to quantitative data, 26% change in performance was attributed to BI capability.

The research's second objective was to ascertain the mediating effect of complementary resources on the relationship between BI capability and firm performance. Based on the results obtained, it was revealed that complementary resources have a positive and significant mediating effect on performance. As indicated in section 6.3.2, a 35% change in firm performance, was attributed to the moderating effect of complementary resources.

The third objective of the research was to examine the moderating effect of organisational capability on the relationship between BI capability and firm performance. Factors under organisation capability include customer, process and performance management capabilities. Based on the discussed results, it was demonstrated that organisational ability has an impact on the relationship between BI capability and performance. The results of the quantitative study (section 6.3.3) revealed that organisational capability accounted for 35.7% of changes in firm performance.

The fourth objective was to examine the combined effect of BI capability, organisational capability and complementary resources on firm performance. The quantitative study results found a positive and significant impact on firm performance than individual effect. The model generated R^2 value of 0.503. It implies 50% of changes in firm performance can be explained by the model. This was backed by the study's qualitative results showing an effect on financial performance, consumer performance, human resources performance and organisation effectiveness.

Figure 6.1 presents the revised framework based on the integrated findings from the qualitative and quantitative strand of this study. The revised framework has distinct advantages over conventional frameworks (for example, Mithas et al., 2011; Isık et al.,

2013) and initial conceptual framework in chapter 2. The framework consists of a broad range of complementary resources that mediate BI impact on firm performance. It comprises validated factors that mediate the benefits that accrue from BI application. Hence, the framework can be used to enhance performance of other firms in Kenya and by extension, to other developing countries, by focusing on the revised indicators of highlighted constructs.

7.3 Conclusion

In spite of ongoing heavy investment in BI tools (Moore, 2017), how BI adds value and actual impact of performance is yet to be addressed adequately in literature (Ida & Graeme, 2015). Empirical studies conducted by various researchers on BI impact, factors that moderate and mediation the relationship between BI and performance, have reported mixed outcomes. Trieu (2017) concluded that BI literature is fragmented and lacks a general framework to incorporate the findings and systematically guide research. Hence, the study was structured with the overall objective of examining the effect of BI capability, complementary resources and organisational capability on performance of firms listed on NSE to mitigate some of the limitations outlined in the extant body of knowledge.

The results of the study, therefore, led to conclusions based on stated objectives. Hence, these conclusions from qualitative and quantitative strands are presented. The findings of the study affirm that BI capability improves firm performance. Thus, in order to improve performance, firms should deliberately develop capabilities by ensuring quality of data collected from external sources is consistently preserved, users have adequate access to the application and the application has the ability to interact with other management systems in the organisation. Firms should also ensure credibility and long-term availability of the vendor selected is assessed, knowledge generated in the organisation is well managed and shared, continuous analytical skills acquisition, the output from BI is used to manage business risks and finally, service level agreement with vendors is explicitly defined.

Furthermore, the results of this study demonstrated a positive mediation effect of complementary resources on the relationship between BI capabilities and firm performance in NSE-listed companies. Hence, to further improve declining performance, firms should develop additional competencies around prevailing culture in the organisation, review the role of BI champions in ensuring they evangelize the use of BI in their sections, enhance rationality in decision making process and review organisation strategy aimed at securing management support in the allocation of resources and setting up a tone at the top on the use of BI across the organisation.

The results in this study have also revealed that the relationship between BI capability and firm performance of companies listed on the NSE is moderated by organisational capabilities. Positive impact on performance is realized when BI out is used to manage performance, process and customer related activities. However, the study also revealed that the combined impact of BI capability, complementary resources and organisational capabilities was positive and significantly greater than the individual effect on firm performance. Hence, for a positive and superior impact on performance, firms should pay special attention to all validated factors in the revised framework.

7. 4 Research Contributions

This section, therefore, presents a contribution to the theory and methodology. It also highlights the implications of study findings for business leaders and policy makers.

7.4.1 Theoretical Contributions

The study's first contribution addresses the theoretical gap at the outset of this thesis. Trieu (2017) observed that BI literature is fragmented and lack a general framework to incorporate the findings and systematically guide research. The study views BI impact in three lenses that is, Information Systems (IS) capability, Knowledge Based Theory (KBT) and the Organisational Learning Theory (OLT). IS Capability theory emphasises on the ability and capacity of the organisation to combine, integrate, review and reconfigure resources as the need arises to gain competitive advantage. This study validated BI capability dimensions identified by Isık et al. (2013). In the revised framework in section 6.5, only six out of nine BI capability dimensions were validated to have a substantial effect on performance. The dimensions include quality of data sources, user access, data reliability, interaction capability, flexibility and risk management. No significant impact was observed on data type, BI expertise and analytical skills. Furthermore, vendor selection, knowledge management and service level agreement emerged as additional significant BI capability dimensions that can enhance performance of firms in developing countries. Olszak (2014) pointed out BI capabilities can be integrated with available organisation resources, to acquire additional VRIN resources. The results confirmed that complementary resources have a significant and positive mediating effect on performance. Moreover, in support of IS capability theory, the complementary impact of constructs in the study is largely attributed to enhanced competitive advantage. Complementary resources are dynamic, complex, ambiguous and therefore, not easy to be imitated by other firms. Deployment of an IT innovation alone is not adequate to improve performance (Peppard & Ward, 2004). Therefore, the study advances knowledge on BI impact by developing an integrated framework that provides a multi-perspective understanding of BI capability for companies listed on NSE.

KBT depicts organisations as a repository of competences and knowledge where knowledge is translated into services and products that have business value, hence impacting positively on firm performance (Kogut & Zander, 1996). Knowledge is perceived to consist of skills, concepts and information corresponding to procedures and declarative differences made in cognitive sciences. It is developed and held by individuals, hence, it has to be managed. Kogut & Zander (1992) assets that the key competitive dimension of a company is to effectively generate and transfer this knowledge within the organisation. The greatest concern in literature on knowledge management is the absence of extensive empirical evidence that knowledge management has on organisational performance (Liu, Song & Cai, 2014). Knowledge management emerged as significant BI dimension in this study. Hence, the current thesis adds to theory and empirical evidence that performance is positively affected by knowledge management. BI focuses on remodeling raw data from internal and external sources into information (knowledge) that is valuable for decision making. In addition, BI provides a platform for sharing generated knowledge to foster innovation and creativity, for example, through well designed reports. Integrated knowledge shared contributes to the enhancement of business processes, products and services, with eventual impact on overall performance (Wang et al., 2014).

Organisational Learning Theory (OLT) asserts that for a firm to survive in a live environment, there is a need for a review of actions and processes that leads to the attainment of the set objectives (Larsen & Eargle, 2015). Hence, for learning to occur, leaders in the organisation must make a conscious decision to change tact in response to rapidly evolving circumstances, connect action to results, and quantify the results. This study has contributed to this theory by providing empirical evidence on the indirect role of organisation learning in enhancing firm performance. For organisational capability to be effective, learning must take place. For example, in performance management, BI provides feedback on revenue by flagging variance on dashboards. In the event of adverse variance, management learn by drilling down to the root causes and take corrective action. The learning process begins with individuals before the acquired knowledge is entrenched within the organisation (Argote, 2011). The result of this study demonstrated that organisational capability has a positive and significant moderating effect on performance.

In summary, this study adds to the existing body of theories by presenting a framework integrating validated moderating and mediating variables that significantly impact the relationship between BI and performance. Additionally, the theoretical proposition and empirical testing of the theories in IS the field has largely focused on the developed countries' context. The research has therefore, added to the literature by integrating data from the developing country context in the broader empirical generalizations of the results.

7.4.2 Knowledge Contributions

The findings of the current study contributed to the knowledge gap that link IS and firm performance by invalidating some earlier conclusions, which found insignificant relationships between IS and performance. For instance, Chae et al. (2014) did not unearth meaningful connection between performance and IT capability in their study. Furthermore, research by Oliveira and Maçada (2017) indicated that IT capability had no direct impact on performance. The results of this study confirmed BI capability has a positive and significant impact on firm performance.

7.4.3 Implications for Managerial Practice

In recent performance challenges experienced by several NSE companies demands that management must take an urgent action to improve profitability and competitiveness to revise downward trend. Due globalisation, shorter product life cycle, shift in social values and demographic patterns, these firms operate in a moderate to rapidly changing business environment hence, the need to develop the capability to detect and respond to such changes. It is clear from the study findings that BI capability has an impact on business performance. The current study has presented optimal BI capabilities, complementary resources, and organisational capability that enhance performance. The teams in the organisation charged with selecting, developing and exploiting BI solutions with be guided by the findings of this study.

Organisational capability is a vital component because it sharps the direction of IT role to the business. The study has established that organisational capability (that consists of customer, process and performance management capabilities), has a positive and significant impact on firm performance. Management of listed companies will be guided by the study to ensure BI is applied in customer management to monitor changes in expectations, trends and service level agreements. Furthermore, effective performance management enabled by BI will enable management to detect unfavourable variations, ascertain sources of variation and implement appropriate strategies to correct the variation in business. BI capability permits a quicker and more responsive redesign and configuration of processes in reaction to shifts in business environment, which in turn enhances organisational performance.

The study has also demonstrated the role of complementary resources in boosting the relationship between BI capability and firm performance. In this study, significant factors under complementary resources comprised decision making process, culture, strategy and

BI champions. The management of listed companies will use this study's findings to ensure that they establish a participative management style in which all ideas are valued. The study provides insight to management to ensure decision making process is driven by facts in addition to aligning IT strategy to overall business strategy. Management will also use these findings to legitimise the selection and development of BI champions across the business. BI champions play a vital role in persuading employees to embrace organisation vision and adopt new technology. The study also offers valuable insight to top management of listed companies of ensuring they provide unwavering support not only during implementation stage, but throughout the system life cycle. To accelerate value from BI and create sustainable competitive advantage, top management support is required in clarifying BI objectives, issuing policy statements relating to BI use, supporing new BI projects financially, making investment in analytically skilled manpower, measuring BI outcomes and seeking facts that support decisions taken by stakeholders.

Triangulated results of this study demonstrated that data type was not a significant factor under BI capability. Consequently, it was dropped from the revised framework. However, studies conducted in other developed countries posit this factor to be significant, for example, Isik et al. (2011). This factor was measured through accuracy, comprehensiveness, consistency and high quality of structured and unstructured data. It implies that management of listed companies can pay special focus on the type of data collected, more so on unstructured data in order to improve performance. Myriad unstructured data sources include web pages with competitor details, emails, sales force documents, internal complaints reports, call center records and research paper collections (Baars & Kemper, 2008; Negash, 2004). 80% of corporate data is estimated to be unstructured and it is growing significantly every day (Gupta & George, 2016; Rogers , 2019). However, it is ignored, due to challenges associated with analysing this type of data. Lang, Ortiz and Abraham (2009) states that output from this type of data can boost quality of early warning in the business.

The overall confirmation of a positive and significant BI impact on performance provides required reference to other individuals spearheading investment in BI solution. BI literature is inconsistent on how BI impact performance. The study also provides significant criteria that management can use to measure the performance impact. The criteria include financial performance, customer performance, human resources and organisation effectiveness.

7.4.4 Implications for Policy

The finding of this research is crucial for policy makers to formulate and improve the current policy frameworks for the listed companies, government and other institutions. First, the study offers empirical evidence that BI capability, complementary resources and organisational capability are critical in enhancing firm performance. Hence, the study accentuates the need for investment in BI solutions. Second, the study provides a solid foundation for policymakers to develop policies that can facilitate exploitation of all those factors identified and presented in the revised framework. For instance, user access under BI capability. Though IS enabled innovations are driving improved performance in business, it has also introduced a range of risks that never existed before due to consolidation of data into a single data base. Data Protection Act, 2019 guarantees every person the right to privacy and obligations of data controllers. The Act provides for severe penalties in the event of infringement of individuals' rights. Hence, the need to design policies that provide for adequate user access while at the same time ensuring data is protected from unauthorized access. Additionally, policies relating to vendor selection will guide stakeholders in the organisation to carry out quality assessment, when selecting vendors who have supplied enterprise resource program (ERP). It emerged from qualitative data analysis that such vendors are sometimes biased towards working with their product hence, limiting connection to other systems due to high integration costs.

Lastly, from a government perspective, provision of a conducive business environment to ensure local firms to remain competitive, amid pressure from cheaper imports has been a challenge, specifically for the manufacturing sector. Findings from this study have shown significant performance effects of the BI. The government, can therefore, devise policies that will make it cheaper for local businesses to acquire BI software. For instance, allowing initial costs as an allowable tax expense. Currently, firms are allowed to capitalize this expense but subsequently recover in five years.

7.4.5 Methodological Contributions

The proposed model offers a point of reference for a wide range of empirical studies that could be performed to further test this model in different areas of study. In arriving at the revised framework, the study adopted mixed methods approach in collecting and analysing data to gain better understanding on impact of BI on performance. The approach provides reliable and richer findings (Mingers, 2003). In particular, the study settled on convergence model. Under this model, the researcher collected and analysed quantitative and qualitative data separately. Finally, the different results were converged during interpretation that resulted in identification new dimensions. The use of mixed methods approach will be a motivator to other researchers in IS research and social science given the paucity of this approach (Mingers, 2001; 2003). Moreover, the study contributed to the literature in the light of the well-known and recognised contextual distinction between "developed countries" and "developing countries", by demonstrating suitability of this approach for research (Avgerou, 2008; Heeks, 2002).

The study adds to PLS-SEM approach empirical studies. SEM is a second-generation tool, an improvement to first generation tools. The first-generation analytical tools assume that data is error-free while SEM recognizes the probability of error and attempts to identify the error component in the measurement model. SEM also enables the assessment of relationships among multiple variables. Furthermore, SEM improves the assessment of mediation. It provides a detailed approach to mediation process. It not only checks for the presence or absence of mediation, but also calculates the degree of Variance Accounted For (VAF). Specifically, the study used smartPLS software in analysing quantitative data. SmartPLS is one of the notable software applications for PLS-SEM. While this application has become popular, available instructional materials on how to carry out the required test is relatively low (Wong, 2013). For those who which to use this software, detailed guidelines on how to run required reports and tests has been summarized in section 3.4.14.

7.5 Limitations of the Study

The researcher faced some limitations in the process of collecting and analysing the data. The instrument, methodology, study timing, and other uncontrollable factors all contribute to the limitations. First, the geographical spread of firms was an obstacle. The study targeted firms listed on NSE, but several of these firms are located in regions far from the city. To access those institutions was a daunting task, which led to a great delay in data collection and processing. Additionally, data collection was very costly due to logistical challenges given that the researcher had no funding support to facilitate this process.

The second limitation was the cross-sectional data used in the analysis. While cross-sectional approach is probably used in research because of ingrained cost and time advantages, it does not have the ability to explore all BI benefits. IT related benefits accrue over a long period of time. Moreover, data was collected in Kenya and that could limit the generalizability of study findings.

Third, data was obtained from individual managers in various departments. For example, IT managers, finance managers, managers of human resources, and operating managers. While it is anticipated that respondents will offer unbiased answers, because of variations in their role and profession, they could have contributed to differing perceptions as to how items in questionnaires were addressed.

Fourth, the study used a five-point Likert scale to collect quantitative data. When using this scale, some respondents do not read carefully the questions and revert by simply ticking the boxes. The researcher rejected one questionnaire because the respondent answered almost all questions with scale numbers, one and two. However, the quality, spirit and letter of the study was not compromised, given the highlighted limitations.

7.6 Suggestions for Further Research

In reference to above limitations, it is possible to classify future research suggestions into three main categories: resolving the shortcomings of the present study, applying this analysis to other applications, and identifying new fields of research applicable to academia and industry. This study, therefore, offers several possibilities for future research.

A cross section design was used for this study hence, data was collected at a specific time. This could have resulted in failure to capture delayed BI performance benefits. BI support is of a long-term nature and cannot fully achieve its benefits within short duration (Audzeyeva & Hudson, 2016). In future research, the longitudinal research design could be used to improve the reliability of performance data. Longitudinal research observes process behaviour and changes in critical variables over time. Venkatesh and Vitalari (1991) observed that longitudinal research is suitable for the information systems field. In terms of development and rollout, information technology is dynamic. Implementation of IT-related project is carried out in a complex organisational environment that has an adverse impact on project maturity to generate value. A longitudinal study using constructs in the revised framework may provide a deeper understanding of BI impact.

New factors emerged during triangulation process from qualitative strand of the study namely; vendor selection, service level agreements, knowledge management and BI champions. It is imperative for future research to validate these factors through quantitative study. Future studies may include more variables that are not included in this research, for example, moderating role of the firm's size. This study collected data from sectors represented on NSE. Future studies should focus on excluded sectors, for example, retail, and compare the results. Furthermore, a similar study can be conducted in other developing countries to further validate the highlighted findings. This research was conducted within the context of Kenyan firms.

Qualitative data for this study was collected through interviews to examine people's views, perceptions, values and motivations of individuals on the research topic. However, the use of two or more forms of data collection, for example, focus groups, enhances the credibility of the study. The literature reveals that, in general, IS research applies different theoretical lenses and methodologies. In guiding this study, IS capability theory, knowledge management theory and organisational learning theory was applied. However, each theoretical lens has some merits and demerits. Therefore, this research topic could be investigated by other theoretical lenses in the future.

Typically, organisations use different BI systems to analyze, present, share and create insights for decision making. It is not clear however, if the impact varies depending on which BI system is in use. Further studies are required to evaluate the impact from same vendor. In summary, given the implications of the study results for managers, policymakers, researchers and academics, a strong foundation for future studies is presented.

7.7 Chapter Summary

The chapters presented a summary of the results in reference to the objectives. Specifically, the chapter discussed the contribution of research findings to theory and methodology. Managerial and policy implication of research findings was also presented. The researcher finally discussed the study limitations and suggestions for further research.

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APPENDICES

APPENDIX I: Questionnaire

This questionnaire is designed to collect data from companies listed on Nairobi Stock Exchange. The purpose of the data is to explain the Impact of Business Intelligence Capabilities on Firm's Performance in Kenya. The data will be used for academic purposes only and will be treated with strict confidence. Your support is highly appreciated.

Section A: Organizational and Respondent Profile

1. Name of the company (Optional)____________________________________

2. Which year was the company incorporated? ____________________________

3. Industry or sector (Please tick)

Agricultural	[ ]	Energy &Petroleum	[ ]
Automobile	[ ]	Insurance	[ ]
Banking	[ ]	Investment	[ ]
Commercial & Services	[ ]	Manufacturing& allied	[ ]
Construction & Allied	[ ]	Telecommunication	[ ]

4. Scope of operation (please tick as appropriate)

National (within Kenya)	[]	Regional (within E.Africa)	[ ]
Regional (within East Africa)	[ ]	Continental (within Africa)	[ ]
Global	[ ]		

6. Number of full time employees____

7. Please indicate your job title/ position__________________________________

8. How long have you worked in this company? (please tick as appropriate)

Less than 5 years	[ ]	6 to 10 years	[ ]
11 to 15 years	[ ]	Over 16 years	[ ]

9. Business Intelligence (BI) tools provides the means for efficient reporting and through analysis of data. What types of BI products/tools are in use in your company? (Multiple answer option)

Microsoft Power BI	[ ]	Tableau	[ ]
Qlik View	[ ]	SAP Business Objects	[ ]

Sisense	[ ]	IBM cognos Analytics	[ ]
Jaspersoft	[ ]	MicroStrategy	[ ]
Oracle analytics server	[ ]	CXO Software	[ ]
Spreadsheets (eg Excel)	[ ]	Others (list here)………………..	

Section B: BI Capability

BI is a broad term that comprises of tools, applications, infrastructure and best practices that provide accessibility and analysis of data to optimize and improve decisions as well as business performance. Examples of advanced BI solutions include power BI, Tableau, quik view and SAP BI. Basic BI solution include spreadsheets for example excel for analysis and generating dashboards. BI capability refers to critical functionalities that help organizations to continually derive and leverage value through for example user access.

2. Please indicate with a tick (√) the extent to which you agree with the following statements on BI Capability. Use the scale where **VLE=Very large extent; LE=Large extent; ME=Moderate extent; SE=Small extent; NT=Not at all**

2: I Data Sources	NT	SE	ME	LE	VLE
Internal data sources quality					
2-1A. The internal data sources used for our BI are readily available					
2-1B. The internal data sources used for our BI are readily usable					
2-1C**.** The internal data sources used for our BI are easy to understand					
2-1D. The internal data sources used for our BI is concise					
Externa Data Sources quality					
2-1E**.**The external data sources used for our BI are readily available					
2-1F**.** The external data sources used for our BI are readily usable					
2-1G.The external data sources used for our BI are easy to understand					
2: 2 Data types	NT	SE	ME	LE	VLE

Quantitative data quality					
2-2A. Our BI provide accurate quantitative data					
2-2B. Our BI provide comprehensive quantitative data					
2-2C. Our BI provide consistence quantitative data					
2-2D. Our BI provide high quality quantitative data					
Qualitative data quality					
2-2E. Our BI provide high quality qualitative data					
2-2F. Our BI provide accurate qualitative data					
2-2G. Our BI provide comprehensive qualitative data					
2-2H. Our BI provide consistent qualitative data					
2: 3 Data Reliability	NT	SE	ME	LE	VLE
Internal data reliability					
2-3A. Internal data collected for our BI is reliable					
2-3B. There are inconsistencies and conflict in the internal data for our BI					
2-3C. Internal data collected for my BI is accurate					
2-3D. Internal data for our BI is updated regularly					
External data reliability					
2-3E. External data collected for our BI is reliable					
2-3FThere are inconsistencies and conflict in the external data for our BI					
2-3G. External data collected for my BI is accurate					
2-3H. External data for our BI is updated regularly					
2: 4 User Access	NT	SE	ME	LE	VLE
2-4A. I’m satisfied with the manner I access my BI					
2-4B. I’m authorised to access to all information I need with BI					
2-4C. The way I access my BI is fits well to the types of decisions I make using my BI					
2: 5 Analytical capability	NT	SE	ME	LE	VLE

2-5A. Our BI system provide a variety of business analytical tools (such as graphs, charts, trends) to analyse the data					
2-5B. Our BI system provides required information in a friendly format					
2:6 Interaction capability	NT	SE	ME	LE	VLE
2-6A. Our BI provides a unified view of the business and data and processes					
2-6B. Our BI provides easy and seamless to data from other application and systems					
2-6C. Our BI provides querying and drill down options					
2:7 Flexibility	NT	SE	ME	LE	VLE
2-7A. Our BI is compatible with other tools that I use (e.g. Microsoft office suite)					
2-7B. Our BI can accommodate changes in business requirements quickly					
2-7C. Our BI is highly scalable with regards to transactions					
2-7D. Our BI is highly scalable with regards to number of users					
2: 8 Risk Management support	NT	SE	ME	LE	VLE
2-8A. Our BI helps me minimize uncertainties in my decision making process					
2-8B. Our BI supports decisions associated with high level of risk (e.g., entering a new market)					
2-8C. Our IT unit provides a wide range of security and risk management services (security policies, disaster planning)					
2: 9 Human Capital	NT	SE	ME	LE	VLE
2-9A Training on the use of BI system is INADEQUATE					

2-9BKey users are technically knowledgeable in exploiting BI capabilities					
2-9C Managers and supervisors have a task of supporting the development of new competencies in their staff.					
2-9D We hold meetings to share own experiences on the use if BI					

Section C: Organisational Capability

Organizational capabilities are competencies that connect firm performance and BI capability. These capabilities include; process management, customer management, performance management capability.

3. Please indicate with a tick (√) the extent to which you agree with the following statements

Key:VLE=Very large extent**; LE=**Large extent**; ME=**Moderate extent**; SE=**Small extent**; NT=**Not at all

Customer Management Capability (CC)	NT	SE	ME	LE	VLE
Use of BI in customer-facing operations has helped us:					
CC1Create a comprehensive customer-related database					
CC2 Deliver customer data to our front-line staff so that they can sell, market and service our customers based on facts					
CC3 Deliver customer data to our marketing, sales and service staff at the right time so that they can cross-sell and up-sell to customers.					
CC4 Conduct intelligent analysis of customer data to guide our marketing and sales efforts					
Process Management Capability (PR)	NT	SE	ME	LE	VLE
Use of BI in Business operations has helped us:					
PR5 Improve efficiency of internal process					

PR6 Increase staff productivity					
PR7 Reduced operation cost					
Performance Management Capability (PM)	NT	SE	ME	LE	VLE
Use of BI in performance management has helped us:					
PM8 To gather data on key performance metrics					
PM9 Monitor key performance metrics					
PM10 To link metric analysis to decision making					

Section D: Complementary Resources

Complementary Organisational resources defines the context in which strategic decisions are made. These firm factors include organizational structure, culture, and management style and employee skills and competencies.

4. Please indicate with a tick (√) the extent to which you agree with the following statements.

Key:VLE=Very large extent**; LE=**Large extent**; ME=**Moderate extent**; SE=**Small extent**; NT=**Not at all

STATEMENT	NT	SE	ME	LE	VLE
Structure					
CS1 We have enabling structures that allow for knowledge sharing and growth					
CS2 My work is subject to a lot of rules and procedures stating how various aspects of my job are to be done					
CS3 There is a culture of continuous improvement, always trying to learn and do better					
CS4 Most people in the organisation have input into the decision that affect them					
Culture	NT	SE	ME	LE	VLE

CO1cooperation and collaboration across functional roles is actively encouraged					
CO2Management does not embrace participative management style where everyone's ideas are valued					
CO3Managers facilitate communication and negotiation rather than exerting top-down control					
CO4 Knowledge sharing is not embedded in our culture					
Organisation strategy	NT	SE	ME	LE	VLE
CH1 Emphasize effective coordination among different functional areas					
CH2 Information systems provide support for decision making					
CH3 Use of cost control systems for monitoring performance					
CH4 We emphasize basic research to provide us with future competitive edge					
CH5 Forecasting key indicators of operations					
CH6 Constantly seeking new opportunities related to the present operations					
CH7 Constantly on the lookout for businesses that can be acquired					
Decision making process	NT	SE	ME	LE	VLE
DP1-A In our organisation, decisions are affected by the use of power among team members					
DP1_B Team members are primarily in concerned with the goals of the organization and not their own goals					
DP1-C Managers in our organisation are open with each other about their interests in the decision.					
DP1-D In our organisation, decisions affected by negotiation among team members.					

DP2-A Top managers rely on personal judgement in making important decisions.					
DP2-B On many occasions, top managers have enough information, but make important decisions based on a 'gut-feeling'.					
DP2-C Top managers place emphasis on past experience in making important decisions.					
DP3-A Managers extensively analyse relevant information before making a decision.					
DP3-B Managers extensively look for relevant information in making a decisions					
DP3-C Managers extensively evaluate available options before making a decisions					

Section E: Firm Performance

5. Please indicate with a tick (√) the extent to which you agree with the following statements

Key:VLE=Very large extent**; LE=**Large extent**; ME=**Moderate extent**; SE=**Small extent**; NT=**Not at all

STATEMENT	NT	SE	ME	LE	VLE
Financial Performance (FP)					
FP1 The firm achieves the set profit targets					
FP2 The return on investment has been growing					
FP3 Growth is sales hit the set target					
FP4 Our assets utilisation index has improved					
Customer Performance (CP)	NT	SE	ME	LE	VLE
CP1 Customer complains has dropped significantly					
CP2 Customer loyalty has improved overtime					
CP3 Number of new customers has been increasing					

Organisational Effectiveness (OE)	NT	SE	ME	LE	VLE
OE1 Our BI has improved efficiency of internal processes					
OE2 Our BI has contributed to cost reduction					
OE3 Our BI has improved coordination with business partners/Suppliers					
OE4 New products are developed frequently					
OE5 Our investment in research and development has intensified					
OE6 Compared to our competitors, our company is more profitable					
0E7 Compared to our competitors, our company is more successful					
HR Performance (HP)	NT	SE	ME	LE	VLE
HP1 Staff consistently demonstrate behaviourfocused on driving exceptional performance					
HP2 Employees focus their energy on fulfilling our collective mission, not on internal politics					
Employee retention is higher than our competitors					
HP3 Employee morale has been growing					
HP4 Employee productivity is low					
HP5 Employee skill development has been intensified					

APPENDIX II: Interview Guide

Section One:

a) Have you even used BI application/tools**(Screening question)**
b) What is your age group?
c) What is your position?

Section Two

BI Capability

(BI is a broad term that comprise of tools, applications, infrastructure and best practices that provide accessibility and analysis of data to optimize and improve decisions as well as business performance. Examples of advanced BI solutions include power BI, Tableau, quik view and SAP BI. Basic BI solution includes spreadsheets for example excel for analysis and generating dashboards. BI capability refers to critical functionalities that help organizations to continually derive and leverage value through for example user access).

a) What can you say about the data sources quality, data type quality, use access, data reliability and interactive capability of Business Intelligence in your organization?
b) What can you say about your knowledge, skills and experience on the use BI system in our organization?
c) What can you say about the flexibility and risk management capabilities of your BI systems?

Organization Capability

Organizational capabilities are competencies that connect firm performance and BI capability. These capabilities include; process management, customer management, performance management capability.

Describe how BI enhance the following capacities in your organization

a) Customer management
b) Process management
c) Performance management

Complementary Resources

(Complementary Organisational resources defines the context in which strategic decisions are made. These firm factors include organizational structure, culture, and management style and polices employee skills and competencies).

Does decision making process, culture, structure and human resources practice mediate the relationship between BI and performance? If yes, how.

Firm Performance

a) Has the BI impacted the following, if yes, how?

- Financial performance
- Organization effectiveness
- Customer
- Human Resources

b) Any other BI impact to your organization

APPENDIX III: letter of Introduction

UNIVERSITY OF NAIROBI

COLLEGE OF HUMANITIES & SOCIAL SCIENCES

SCHOOL OF BUSINESS

Telephone: 4184160-5 Ext 215
Telegrams: "Varsity" Nairobi
Telex: 22095 Varsity

P.O. Box 30197
Nairobi, KENYA

11th July, 2019

TO WHOM IT MAY CONCERN

INTRODUCTORY LETTER FOR RESEARCH
EDWARD CHAMWADA BUHASO REGISTRATION NO. D80/72467/2011

The above named is a registered PhD candidate at the University of Nairobi, School of Business. He is conducting research on *"Business Intelligence Capability, Organizational Capability, Complementary Resources and Performance of Firms Listed at the Nairobi Securities Exchange"*.

The purpose of this letter is to kindly request you to assist and facilitate the student with necessary data which forms an integral part of the thesis. The information and data required is needed for academic purposes only and will be treated in **Strict-Confidence**.

Your co-operation will be highly appreciated.

Prof. Mary Kinoti
Associate Dean, Graduate Business Studies
School Of Business

MK/jm

UNIVERSITY OF NAIROBI
11 JUL 2019
SCHOOL OF BUSINESS
P.O. Box 30197-00100, NAIROBI

APPENDIXIV: Listed Companies

	AGRICULTURAL-(6)		ENERGY & PETROLEUM-(5)
	Williamson Tea ltd Eaagads Ltd The Limuru Tea Co. Ltd Kakuzi Ltd Kapchorua Tea Co. Ltd Sasini Ltd		Umeme Limited Total Kenya Limited Kenya Power & Lighting Limited KenolKobil Ltd Ord KenGen Co. Ltd
	AUTOMOBILES & ACCESSORIES-(1)		INSURANCE-(6)
	Car & General (K) Ltd		Kenya Re Jubilee Holdings Ltd CIC Insurance Group British-American Investments Co.(Kenya) Ltd Liberty Kenya Holdings Ltd Sanlam Kenya
	BANKING-(12)		INVESTMENT-(6)
	Kenya Commercial Bank Ltd The Co-operative Bank of Kenya NIC Bank Ltd I&M Holdings Ltd Equity Bank Ltd Standard Chartered Bank Kenya Ltd Diamond Trust Bank Kenya Ltd National Bank of Kenya Ltd Housing Finance Co.Kenya Ltd Barclays Bank of Kenya Ltd CFC Stanbic of Kenya Holdings Ltd BK Group		Centum Investment Co Ltd Home Afrika Ltd Kurwitu Ventures Ltd Olympia Capital Holdings Ltd Trans-Century Ltd Nairobi Security Exchange
	COMMERCIAL AND SERVICES-(13)		MANUFACTURING & ALLIED-(8)
	Standard Group Ltd WPP Scangroup Ltd Nation Media Group Ltd TPS Eastern Africa Ltd Nairobi Business Ventures Ltd Longhorn Kenya Ltd Uchumi Supermarket Ltd Kenya Airways Ltd Express Kenya Ltd Ord Atlas African Industries Ltd Deacons (East Africa) Eveready EA Sameer Africa		Unga Group Ltd Carbacid Investments Ltd Mumias Sugar Co. Ltd Kenya Orchards Ltd Ord Flame Tree Group East African Breweries Ltd British American Tobacco Kenya Ltd B.O.C Kenya Ltd
	CONSTRUCTION & ALLIED-(6)		TELECOMMUNICATION (1)
	Crown Paints Kenya Ltd E.A.Portland Cement Co. Ltd Bamburi Cement Ltd ARM Cement Ltd E.A.Cables Ltd Stanlib Fahari		Safaricom Ltd

APPENDIXV: Sample Extract From Atlas.ti

Document	Quotation Content	Codes	Reference
B3	It is only used for business planning whereby we are able to know that probably we expect such opportunities from such and such customers but it will not be used to probably at a bigger extent to analyze the customer needs	Performance monitoring	4037 - 4259
B5	So basically I will be right to say that this output helps you to monitor the key performance indicators for the business	Key performance Indicators Performance monitoring	8700 - 8820
B5	informs me that I have a market that has emerged and I need to go there and identify what's happening	Performance monitoring	12889 - 12990
B7	So for us the end goal is giving actionable insight to the leadership and more as a strategic or leadership tool than an operational tool	Performance monitoring	5606 - 5744
B7	the beauty of it is that you are able based on the trend to run a report in the future e.g when you put in a pricing risk based on the average run rate of say the loss ratio are able to see may be when you put in a 5% based on the average what it would mean in terms of profitability	Performance monitoring	6116 - 6399
B8	we also report at reporting market intelligence	Performance monitoring	3112 - 3159
B8	In deed those risk management are put in and once a customer has been brought in from a risk rating you can say the likelihood of this customer defaulting so give him a higher risk factor financial default which will now change his matrix of what would be the charge out rate.	Performance monitoring	6473 - 6751
B8	So anytime there's an element its flagged out you can put up in triggers which can say the element of this customer is not resolved within 24hours is an escalation matrix and is escalated to the right person	Performance monitoring	7292 - 7498
B8	more importantly you are able to go back to history and compare change and value and map it to the environment to forecast what the future will be like and also it can be used to be able to address emerging issues	Business plan Performance monitoring	11730 - 11942

APPENDIX VI: Skewness and Kurtosis

Items	**Loading**	**N**	**Mean**	**Std. Deviation**	**Skewness**		**Kurtosis**	
BI Capability		**Statistic**	**Statistic**	**Statistic**	**Statistic**	**Std. Error**	**Statistic**	**Std. Error**
2-1A. The internal data sources used for our BI are readily available	0.722	55	4.00	.694	.000	.322	-.853	.634
2-1B. The internal data sources used for our BI are readily usable	0.650	55	3.95	.731	.085	.322	-1.080	.634
2-4B. I'm authorised to access to all information I need with BI	0.789	55	3.56	.977	.000	.322	-.965	.634
2-4C. The way I access my BI is fits well to the types of decisions I make using my BI	0.733	55	3.47	.813	.198	.322	-.387	.634
2-5A. Our BI system provide a variety of business analytical tools (such as graphs, trends) to analyse the data	0.698	55	3.60	1.011	-.228	.322	-.520	.634
2-5B. Our BI system provides required information in a friendly format	0.728	55	3.58	.854	.198	.322	-.655	.634
2-6A. Our BI provides a unified view of the business and data and processes	0.694	55	3.09	.776	.578	.322	.373	.634
2-6B. Our BI I'm authorised to access to all information I need with BI	0.656	55	3.15	.678	.554	.322	.895	.634
2-8A. Our BI helps me minimize uncertainties in my decision making process	0.701	55	3.51	.814	-.137	.322	-.408	.634
2-8B. Our BI supports decisions associated with high level of risk (e.g., entering a new market)	0.731	55	3.35	.927	-.612	.322	.018	.634
2-8C. Our IT unit provides a wide range of security and risk management services (security policies, disaster planning)	0.728	55	3.40	.852	-.142	.322	.292	.634
Organisational Capability								
CC1Create a comprehensive customer-related database	0.806	55	3.51	.879	-.029	.322	.201	.634
CC2 Deliver customer data to our front-line staff so that they can sell, market and service our customers based on facts	0.815	55	3.42	.854	-.013	.322	-.578	.634
CC3 Deliver customer data to our marketing, sales and service staff at the right time so that they can cross-sell and up-sell to customers.	0.885	55	3.42	1.066	-.444	.322	-.230	.634
CC4 Conduct intelligent analysis of customer data to guide our marketing and sales efforts	0.834	55	3.55	.919	-.287	.322	-.016	.634
PR5 Improve efficiency of internal process	0.715	55	3.56	.764	.424	.322	-.432	.634
PM8 To gather data on key performance metrics	0.580	55	3.42	.712	.140	.322	-.100	.634
PM10 To link metric analysis to decision making	0.648	55	3.51	.858	.062	.322	-.563	.634
Complementry Resources								
CS3 There is a culture of continuous improvement, always trying to learn and do better	0.655	55	3.62	.733	.159	.322	-.339	.634
CH1 Emphasize effective coordination among different functional areas	0.777	55	3.53	.663	.491	.322	-.220	.634
CH2 Information systems provide support for decision making	0.737	55	3.69	.605	.255	.322	-.573	.634
CH3 Use of cost control systems for monitoring performance	0.665	55	3.44	.764	-.424	.322	-.432	.634
CH4 We emphasize basic research to provide us with future competitive edge	0.641	55	3.24	.769	.069	.322	1.004	.634
CH6 Constantly seeking new opportunities related to the present operations	0.828	55	3.51	.814	.505	.322	-.439	.634
CH7 Constantly on the lookout for businesses that can be acquired	0.769	55	3.60	.894	-.071	.322	-.688	.634
DP2-B On many occasions, top managers have enough information, but make important decisions based on a 'gut-feeling'?	0.630	55	3.85	.803	-.394	.322	-.122	.634
DP3-A Managers extensively analyse relevant information before making a decision.	0.725	55	3.84	.739	.273	.322	-1.100	.634
Firm Performance								
FP2 The return on investment has been growing	0.594	55	3.18	.772	.172	.322	-.344	.634
CP1 Customer complains has dropped significantly	0.726	55	3.27	.891	-.250	.322	-1.155	.634
CP2 Customer loyalty has improved overtime	0.653	55	3.36	.754	.082	.322	-.235	.634
OE1 Our BI has improved efficiency of internal processes	0.779	55	3.76	.769	-.069	.322	-.416	.634
OE3 Our BI has improved coordination with business partners/Suppliers	0.807	55	3.40	.894	.071	.322	-.688	.634
OE4 New products are developed frequently	0.778	54	3.04	.910	.548	.325	.283	.639
HP1 Staff consistently demonstrate behaviourfocused on driving exceptional performance	0.654	55	3.42	.712	-.499	.322	-.416	.634

APPENDIX VII: Retained/dropped Measures

CONSTRUCT	DIMENSION	MEASURES	Loadings	Decision
BI Capability	Data Sources **	**2-1A. The internal data sources used for our BI are readily available**	**0.722**	**Retained**
		2-1B. The internal data sources used for our BI are readily usable	**0.650**	**Retained**
		2-1C. The internal data sources used for our BI are easy to understand	<0.590	Dropped
		2-1D. The internal data sources used for our BI is concise	<0.590	Dropped
		2-1E.The external data sources used for our BI are readily available	<0.590	Dropped
		2-1F. The external data sources used for our BI are readily usable	<0.590	Dropped
		2-1G.The external data sources used for our BI are easy to understand	<0.590	Dropped
	Data types *	2-2A. Our BI provide accurate quantitative data	<0.590	Dropped
		2-2B. Our BI provide comprehensive quantitative data	<0.590	Dropped
		2-2C. Our BI provide consistence quantitative data	<0.590	Dropped
		2-2D. Our BI provide high quality quantitative data	<0.590	Dropped
		2-2E. Our BI provide high quality qualitative data	<0.590	Dropped
		2-2F. Our BI provide accurate qualitative data	<0.590	Dropped
		2-2G. Our BI provide comprehensive qualitative data	<0.590	Dropped
		2-2H. Our BI provide consistent qualitative data	<0.590	Dropped
	Data Reliability *	2-3A. Internal data collected for our BI is reliable	<0.590	Dropped
		2-3B. There are inconsistencies and conflict in the internal data for our BI	<0.590	Dropped
		2-3C. Internal data collected for my BI is accurate	<0.590	Dropped
		2-3D. Internal data for our BI is updated regularly	<0.590	Dropped
		2-3E. External data collected for our BI is reliable	<0.590	Dropped
		2-3FThere are inconsistencies and conflict in the external data for our BI	<0.590	Dropped
		2-3G. External data collected for my BI is accurate	<0.590	Dropped
		2-3H. External data for our BI is updated regularly	<0.590	Dropped
	User Access **	2-4A. I'm satisfied with quality of the way I access my BI	<0.590	Dropped
		2-4B. I'm authorised to access to all information I need with BI	**0.789**	**Retained**
		2-4C. The way I access my BI is fits well to the types of decisions I make using my BI	**0.733**	**Retained**
	Analytical capability *	**2-5A. Our BI system provide a variety of business analytical tools (such as graphs, trends) to analyse the data**	**0.698**	**Retained**
		2-5B. Our BI system provides required information in a friendly format	**0.728**	**Retained**
	Interaction capability **	**2-6A. Our BI provides a unified view of the business and data and processes**	**0.694**	**Retained**
		2-6B. Our BI I'm authorised to access to all information I need with BI	**0.656**	**Retained**
		2-6C. The way I access my BI is fits well to the types of decisions I make using my BI	<0.590	Dropped
	Flexibility *	2-7A. Our BI is compatible with other tools that I use (e.g. Microsoft office suite)	<0.590	Dropped
		2-7B. Our BI can accommodate changes in business requirement quickly	<0.590	Dropped
		2-7C. Our BI is highly scalable with regards to transactions	<0.590	Dropped
		2-7D. Our BI is highly scalable with regards to uses	<0.590	Dropped
	Risk Management support **	**2-8A. Our BI helps me minimize uncertainties in my decision making process**	**0.701**	**Retained**
		2-8B. Our BI supports decisions associated with high level of risk (e.g., entering a new market)	**0.731**	**Retained**
		2-8C. Our IT unit provides a wide range of security and risk management services (security policies, disaster planning)	**0.728**	**Retained**
	BI Experience *	2-9A Training on the use of BI system is INADEQUATE	<0.590	Dropped
		2-9BKey users are technically knowledgeable in exploiting BI capabilities	<0.590	Dropped
		2-9C Managers and supervisors have a task of supporting the development of new competencies in their staff.	<0.590	Dropped
		2-9D We hold meetings to share own experiences on the use of BI	<0.590	Dropped

Organisational Capability	Customer Management Capability **	**CC1Create a comprehensive customer-related database**	**0.806**	**Retained**
		CC2 Deliver customer data to our front-line staff so that they can sell, market and service our customers based on facts	**0.815**	**Retained**
		CC3 Deliver customer data to our marketing, sales and service staff at the right time so that they can cross-sell and up-sell to customers.	**0.885**	**Retained**
		CC4 Conduct intelligent analysis of customer data to guide our marketing and sales efforts	**0.834**	**Retained**
	Process Management Capability (PR) **	**PR5 Improve efficiency of internal process**	**0.715**	**Retained**
		PR6 Increase staff productivity	<0.590	Dropped
		PR7 Reduced operation cost	<0.590	Dropped
	Performance Management Capability **	**PM8 To gather data on key performance metrics**	**0.680**	**Retained**
		PM9 Monitor key performance metrics	<0.590	Dropped
		PM10 To link metric analysis to decision making	**0.648**	**Retained**
Complementary Resources	Structure *	CS1 We have enabling structures that allow for knowledge sharing and growth	<0.590	Dropped
		CS3 There is a culture of continuous improvement, always trying to learn and do better	**0.655**	**Retained**
		CS4 Most people in the organisation have input into the decision that affect them	<0.590	Dropped
	Culture **	CO1cooperation and collaboration across functional roles is actively encouraged	<0.590	Dropped
		CO2Management does not embraces participative management style where everyone's ideas are valued	<0.590	Dropped
		CO3Managers facilitate communication and negotiation rather than exerting top-down control	<0.590	Dropped
		CO4 Knowledge sharing is not embedded in our culture	<0.590	Dropped
	Organisation strategy **	**CH1 Emphasize effective coordination among different functional areas**	**0.777**	**Retained**
		CH2 Information systems provide support for decision making	**0.737**	**Retained**
		CH3 Use of cost control systems for monitoring performance	**0.665**	**Retained**
		CH4 We emphasize basic research to provide us with future competitive edge	**0.641**	**Retained**
		CH5 Forecasting key indicators of operations	<0.590	Dropped
		CH6 Constantly seeking new opportunities related to the present operations	**0.828**	**Retained**
		CH7 Constantly on the lookout for businesses that can be acquired	**0.769**	**Retained**
	Decision making process **	DP1_B Team members are primarily in concerned with the goals of the organization and not their own goals	<0.590	Dropped
		DP1-C Managers in our organisation are open with each other about their interests in the decision.	<0.590	Dropped
		DP1-D In our organisation, decisions affected bynegotiation among team members.	<0.590	Dropped
		DP2-A Top managers rely on personaljudgement in making important decisions.	<0.590	Dropped
		DP2-B On many occasions, top managers have enough information, but make important decisions based on a 'gut-feeling'?	0.630	**Retained**
		DP2-C Top managers place emphasis onpast experience in making important decisions.	<0.590	Dropped
		DP3-A Managers extensively analyse relevant information before making a decision.	0.725	**Retained**
		DP3-B Managers extensively look for relevant information in making a decisions	<0.590	Dropped
		DP3-C Managers extensively look for relevant information in making a decisions	<0.590	Dropped
Firm Performanc	Financial Performance **	FP1 The firm achieves the set profit targets		
		FP2 The return on investment has been growing	0.594	**Retained**
		FP3 Growth is sales hit the set target	<0.590	Dropped
		FP4 Our assets utilisation index has improved	<0.590	Dropped
	Customer Performance **	**CP1 Customer complains has dropped significantly**	0.726	**Retained**
		CP2 Customer loyalty has improved overtime	0.653	**Retained**
		CP3 Number of new customers has been increasing	<0.590	Dropped

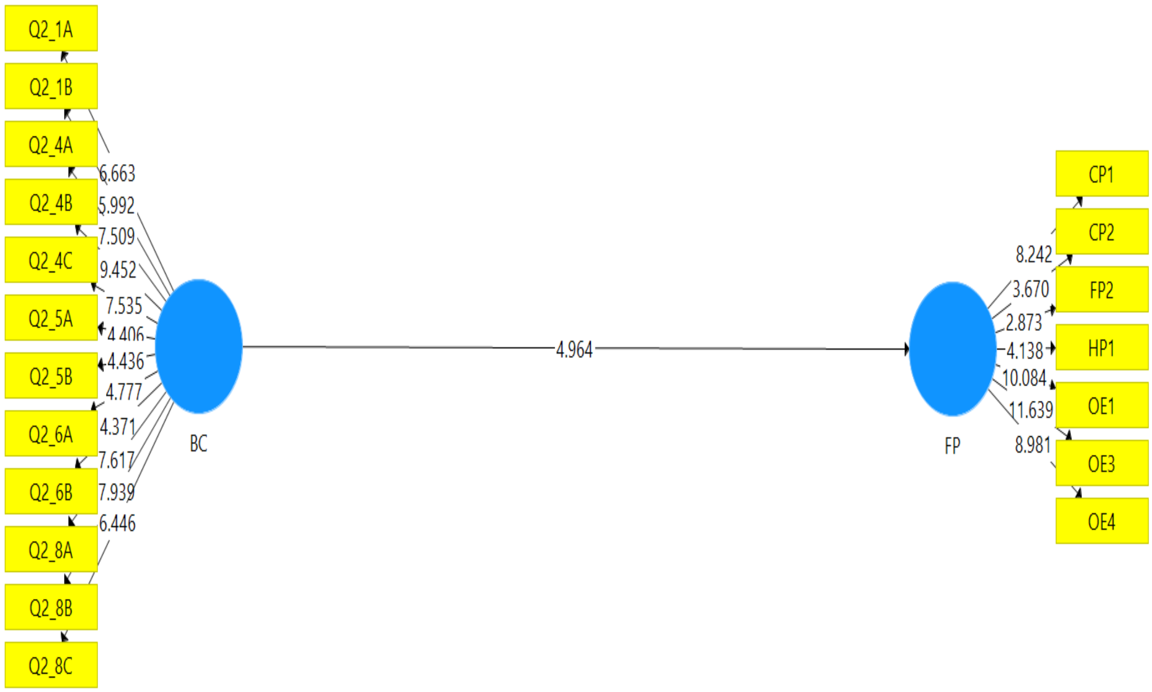
	Organisational Effectiveness **	**OE1 Our BI has improved efficiency of internal processes**	0.779	**Retained**
		OE2 Our BI has contributed to cost reduction	<0.590	Dropped
		OE3 Our BI has improved coordination with business partners/Suppliers	**0.807**	**Retained**
		OE4 New products are developed frequently	**0.778**	**Retained**
		OE5 Our investment in research and development has intensified	<0.590	Dropped
		OE6 Compared to our competitors, our company is more profitable	<0.590	Dropped
		0E7 Compared to our competitors, our company is more successful	<0.590	Dropped
	HR Performance **	**HP1 Staff consistently demonstrate behaviourfocused on driving exceptional performance**	0.654	**Retained**
		HP2 Employees focus their energy on fulfilling our collective mission, not on internal politics	<0.590	Dropped
		HP3 Employee retention is higher than our competitors	<0.590	Dropped
		HP4 Employee morale and has been growing	<0.590	Dropped
		HP6 Employee skill development has been intensified	<0.590	Dropped

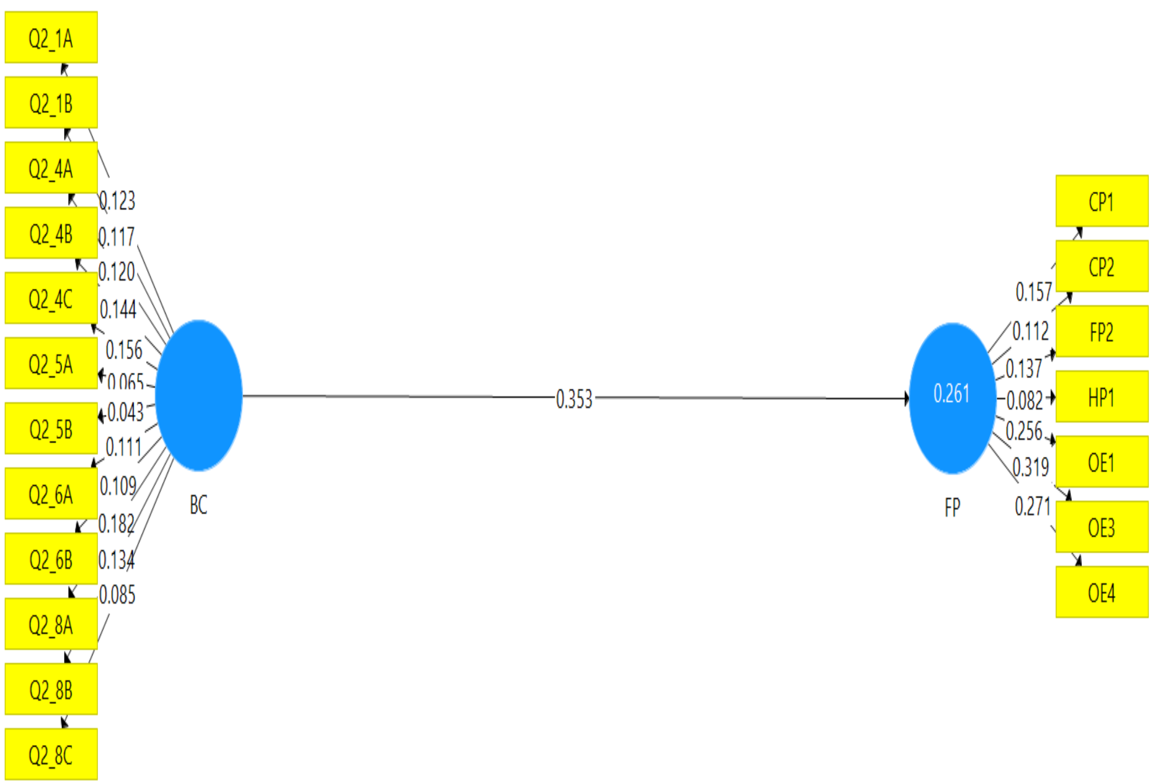
Note: * Dropped

** Retained

APPENDIX VIIIa:Direct relation between BC and FP

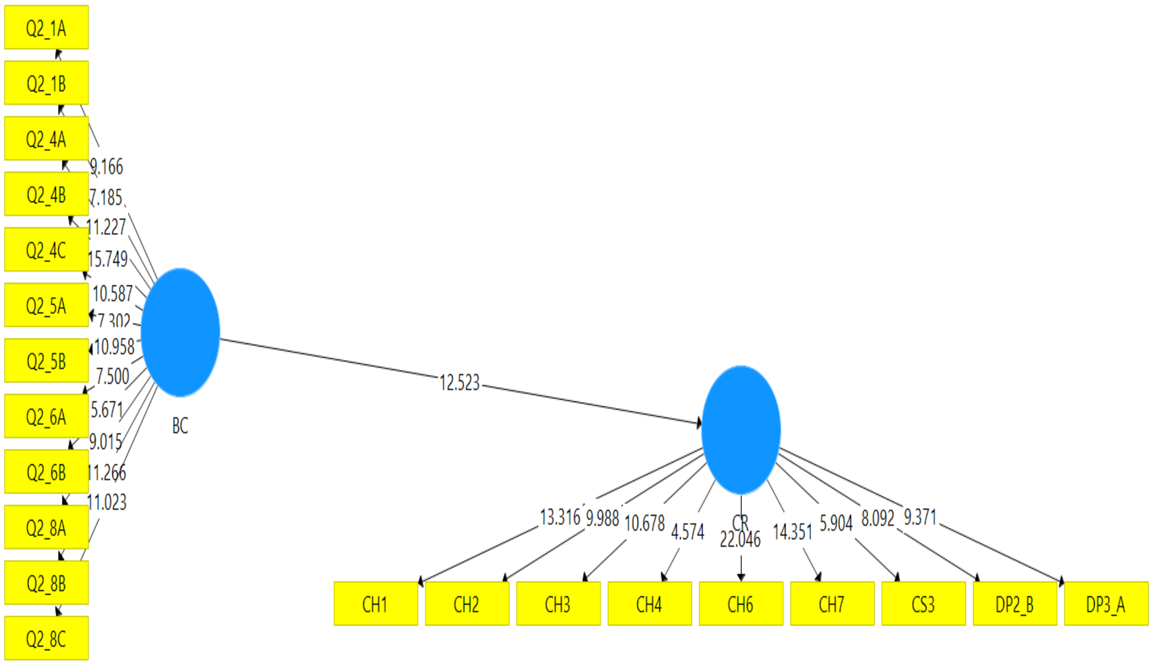
Step1 : PLS-SEM: Beta value = 0.353 and Bootstrap t-value =4.964

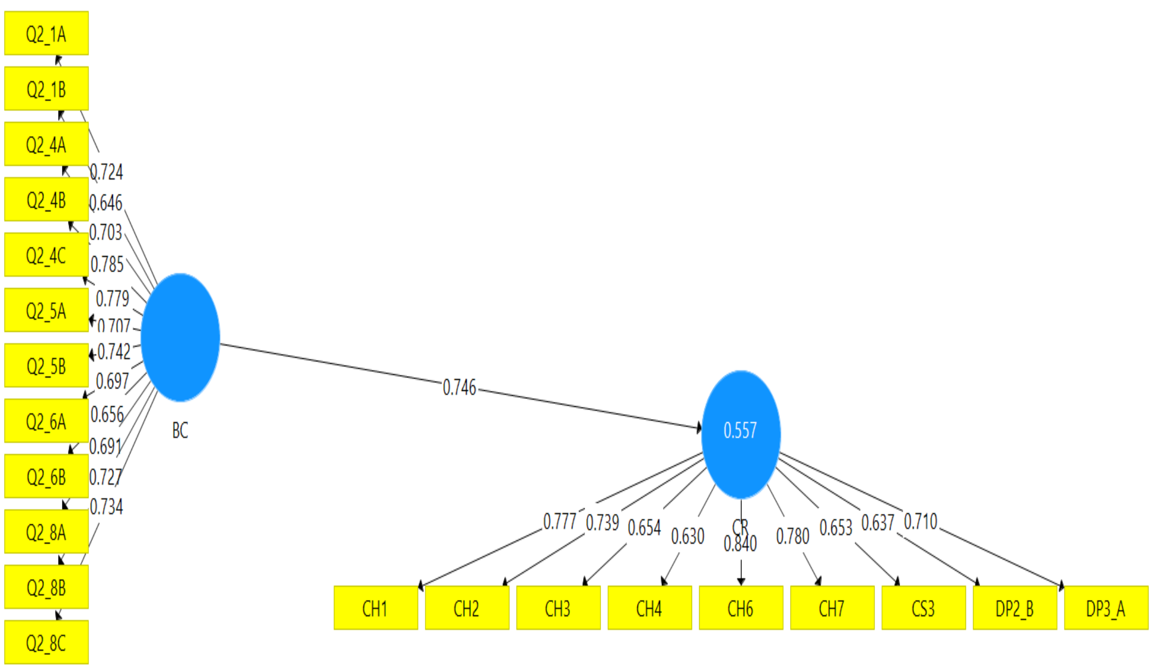




APPENDIX VIIIb: Direct path between BC and CR

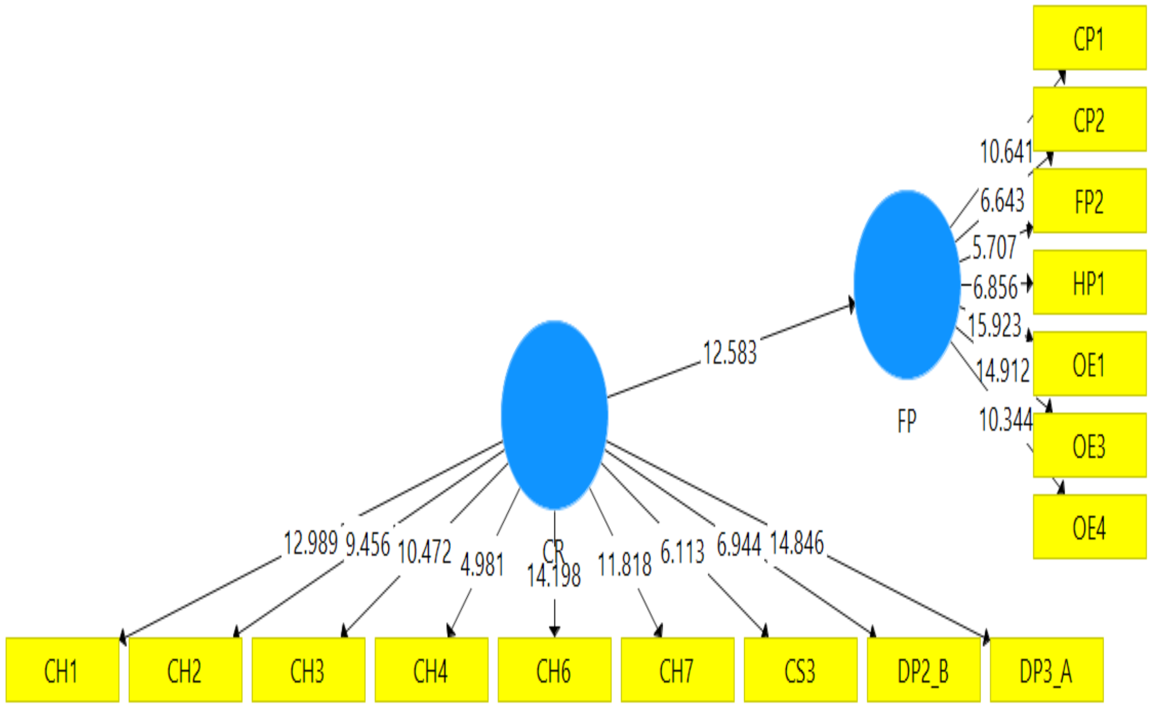
Step2 : PLS-SEM: Beta value = 0.746 and Bootstrap t-value =12.523

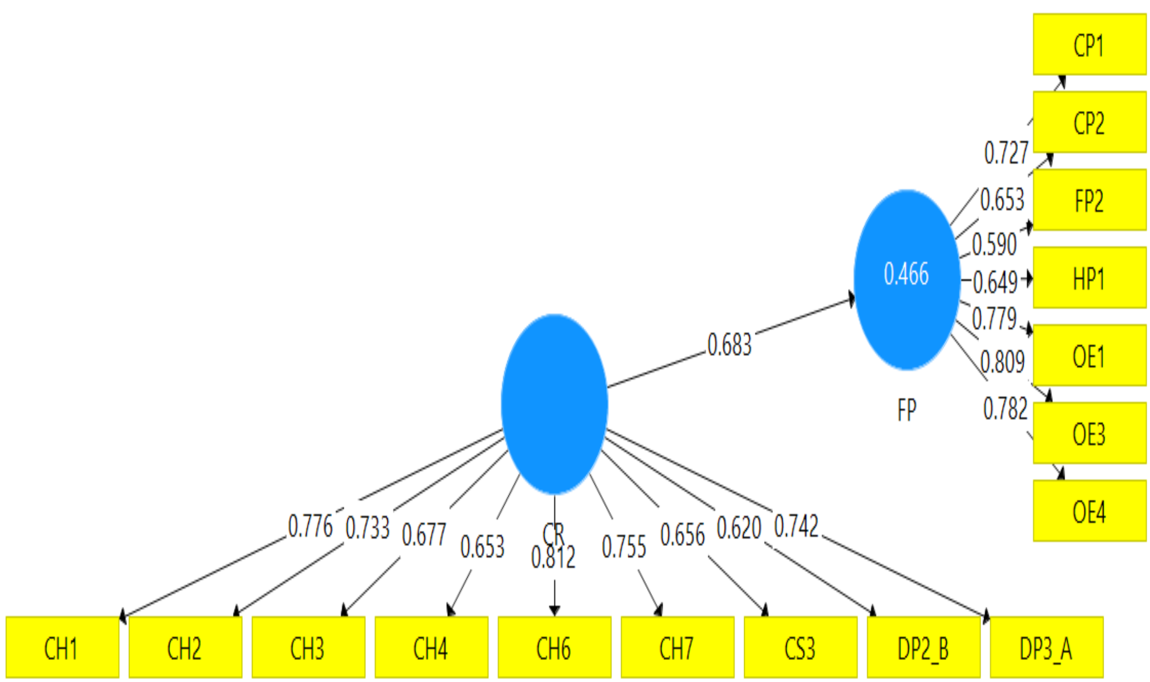




APPENDIX VIIIc: Direct path between CR and FP

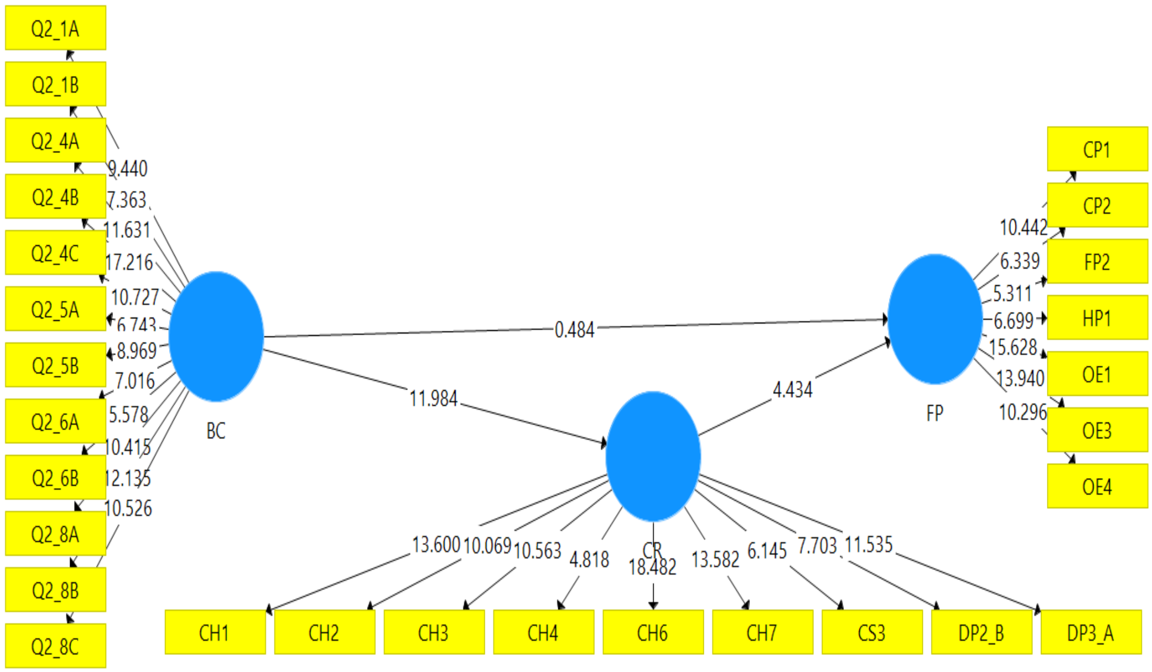
Step3 : PLS-SEM: Beta value = 0.683 and Bootstrap t-value =12.583

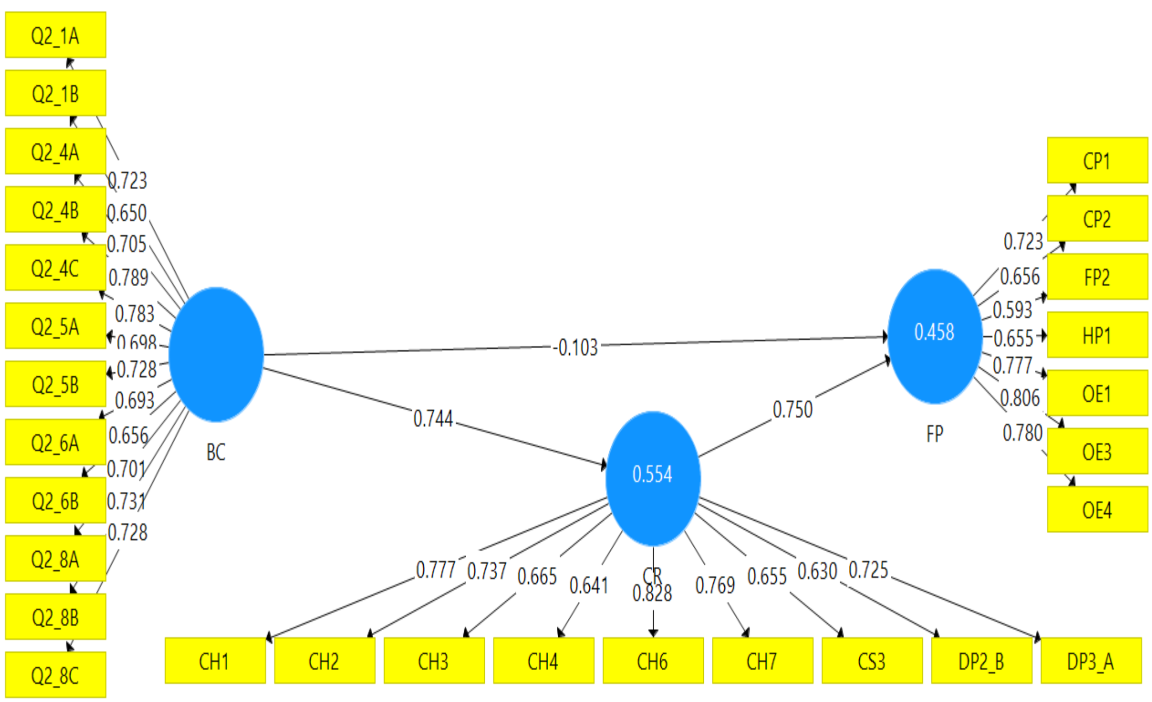




APPENDIX VIIId: Indirect path between BC, OC and FP

Step4 : PLS-SEM: Beta value = -0.103 and Bootstrap t-value =0.484





APPENDIX IX: Enumeration of Themes

DIMENSION	THEMES FREQUENCE					% SCORE	REMARKS	
Data source quality**	B3	B7	B5	B4	B2	63%	SF	Retained
Data type quality*	B3	B6				25%	NS	Dropped. Qualitative data depend on the BI tool in use
User access**	B3	B4	B8	B2		50%	SF	Retained
Data reliability**	B6	B3	B4	B5		50%	SF	Retained
Interaction capability**	B2	B6	B7	B4		50%	SF	Retained
Vendor selection ***	B7	B4	B1	B2		50%	SF	Retained
Analytical skills **	B5	B8	B7	B4		50%	SF	Retained
BI experience*	B8					13%	NS	Dropped
Knowledge Management***	B2	B8	B1	B5		50%		Retained
Flexibility**	B7	B6	B8	B4		50%	SF	Retained
Risk management **	B3	B5	B8	B2		50%	SF	Retained
Service level agreements***	B5	B2	B8	B4	B7	63%	SF	Retained
Customer management**	B3	B2	B8	B4	B5	63%	SF	Retained
Process management**	B5	B8	B4	B2		50%	SF	Retained
Performance management**	B3	B5	B7	B4	B6	63%	SF	Retained
Decision making process**	B2	B3	B4	B5		50%	SF	Retained
Culture**	B3	B2	B6	B4		50%	SF	Retained
Structure*	B8	B2	B4			38%	NS	Did not confirm if the structure has an impact on BI rollout
Organisation strategy**	B7	B2	B3	B4	B8	63%	SF	Retained
Top Management support***	B2	B1	B4	B3	B2	63%	SF	Retained
BI champions***	B4	B7	B4	BI		50%	SF	Retained
Financial performance**	B3	B4	B2	B5		50%	SF	Retained
Customer performance**	B5	B4				25%	NS	Dropped
HR performance**	B2	B5	B3	B4	B8	63%	SF	Retained
Organisation effectiveness**	B5	B2	B8	B4	B7	63%	SF	Retained

APPENDIX X: Research Licence

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