Design Science Research Approach Towards the Construction of Competitive Intelligence Process Model in the Era of Big Data

Submitted for the Degree of
Doctor of Business Administration
At the University of Northampton

2022

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Abstract

Big Data Analytics (BDA) is considered as one of the most recent suites of innovations that benefits a diverse range of businesses and industries. Advanced software systems significantly reduce analytic time, giving organisations the ability to make quick decisions that help to enhance business performance. Uncovering hidden patterns from large amount of data brought out the popularity of BDA term. These analyses can observe the patterns of consumers and customer's trends and provide meaningful insights for marketing teams within organisations. Accordingly, organisations have realised that they must adopt new technological approaches to market their products to create a competitive advantage. Marketers in different sectors put together valuable customer databases to deliver tailored offers and campaigns. The benefits of BDA have also informed new approaches for businesses to stand out. Identifying the right target customer has become one of the strategic objectives within several organisations. Knowing your customers and browsing their behaviour is a phenomenal competitive intelligence, triggering brand loyalty and customer satisfaction. Having top-notch competition and market intelligence requires powerful capabilities. Most organisations pursue to harness that data and extract value from it. To this end, the question is "how"?

This study aims to explore how BDA can be integrated into the competitive intelligence process to achieve best practice of business performance through an adequate decision-making structure. It looks into the development of a conceptual model that incorporates BDA stages and competitive intelligence processes. The context for this research is focused on real estate businesses in the UAE, nonetheless, the findings from this study can also be generalised to other subject areas. The approach used for developing the model is design science research. A comprehensive thematic literature review was conducted to assess existing models and identify main variables of the competitive intelligence process. The result of the literature review reveals that there did not exist a comprehensive model incorporating the dimensions of BDA and competitive intelligence. The variables and their interactions from the literature

informed a proposed conceptual model (CCIP-BDABM), that fills the literature gap and provides solutions for the practice.

Semi structured interviews conducted with leading experts within the intended user community to demonstrate the proposed CCIP-BDABM feasibility and efficacy. Twenty-seven iterative interviews have been conducted aiming to assess and evaluate the model. The outcomes of this study contribute to constructing an artefact model of solutions for adopting BDA in the competitive intelligence process. The real estate industry, in UAE, will benefit from elements, cycles, stakeholder and deliverables as a guidebook of big data investment. Also, the model developed represents conceptual gains for the theory. Moreover, the design science research methodology is historically applied in information systems research projects, however similar to very few existing literatures that adopted design science research, this study also provides a methodological novelty through the application of DSR in an unfamiliar context.

Acknowledgement

I start by thanking ALLAH s.w.t for giving me the passion, strength, courage and stamina throughout this DBA journey.

I am most grateful to my parents; my father taught me how to best navigate through life's choices, to be determined and to communicate with clarity, and most importantly, to never leave any work undone. I must admit, without his early plans for me and my determination to continue studying and working at the same time, I would not be writing this thesis, and I would not be running my own business either. My mother taught me the importance of gratitude and humility, how to love and how to forgive and how to be at peace simply by her touch. May God rest her beautiful soul in peace until the day our souls reunite.

I would like to extend my special thanks to my research supervisor, Professor Amin Hosseinian-Far, for his immense support. I am very grateful for his inspiration, guidance and attention to detail, which has enhanced my writing skills and encouraged me to complete my study with merit. Indeed, I am proud that he is my research supervisor. I would also like to express my appreciation to Dr Dilshad Sarwar for being so supportive, giving insightful ideas and sentimental support throughout this journey.

My husband, Khaldoun, special thanks for his love, unmatched patience, caring, and understanding throughout this tough journey. Thank you for believing in me and for providing me with the time and space needed to face the obstacles along the journey. I am grateful to my wonderful three children; my eldest, Zaid, he is my backbone. My middle, Talya, she is my soulmate. My youngest, Omar, he is my joy. Every day I see more of myself in each of them. Home is not only a place to reside but also wherever they may be.

Declaration

This thesis is submitted for the University of Northampton for the award of Doctor of Business Administration degree. The work presented was carried out under the supervision of Prof. Amin Hosseinian-Far and Dr Dilshad Sarwar within the University of Northampton. I here declare that the work presented in this thesis was the result of my own work. There is no portion of the work covered in this thesis that has been submitted in support of any application for other degree or qualification at this or other institutions of higher learning.

Eman Reda

18th October 2022

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[1] Author's surname has changed between the years 2019 and 2020.

[2] Author's surname has changed between the years 2019 and 2020.

Keywords

Competitive Intelligence (CI), Competitive Intelligence Process (CI Process), Big Data (BD), Big Data Analytics (BDA), Decision-Making, Decision-Makers, Top Management Support, Organisational Agility (OA), Knowledge, Dynamic Capabilities, Competitive Intelligence Environment, Talent Management, Marketing Mix, Design Science Research (DSR), Data Collection, Data Capturing, Data Storing, Data sorting, Data Analytics, Data Automation, Marketing Reports, Channel Dissemination.

List of Acronyms

CI - Competitive Intelligence

BD - Big Data

BDA - Big Data Analytics

TM - Talent Management

CEO - Chief Executive Officer

CFO - Chief Financial Officer

COO - Chief Operating Officer

CCO - Chief Commercial Officer

CIO - Chief Information Officer

CTO - Chief Technology Officer

CMO - Chief Marketing Officer

IT - Information Technology.

BI - Business Intelligence

HR - Human resources

KBV - Knowledge Based View

RBV - Resource Based View

DC - Dynamic Capability

SWOT - Strengths, Weaknesses, Opportunities, and Threats

VRIN - Valuable, Rare, Inimitable and Not substitutable resources

Chapter 1 - Introduction

1.1 Preamble

In the era of big data analytics (BDA), many businesses compete with each other, and gaining competitive intelligence plays a vital role in gaining a competitive advantage. Organisations' tend to understand their customers and their needs to empower their data-driven decisions. Customised dashboards and automated marketing campaigns are the uttermost of big data utilisation. This study looks to establish competitive intelligence process while utilizing BDA, to best achieve marketing goals and outcomes.

This chapter provides an introduction to the topic and context and discusses the researcher’s motivation. Next, it discusses the research gap, question, and problem. Finally, it introduces the research methodology, the contribution to knowledge and professional practice, and ethical considerations, and provide the thesis structure.

1.2 Background

Competitive intelligence (CI) has been the ultimate process for decision-makers who seek to enhance their organisation’s market share. Two decades ago, marketing and strategic planning departments mostly controlled CI operations internally, without the need for interventions and/or insights from third parties (Amos, 2011). At that time, the aim of CI was to provide information about new product launches by competitors, and to investigate the ability of competitors to imitate products (Cook and Schoffro, 1998). Nowadays, organisations are overwhelmed by large quantities of market information, and decision-makers have become concerned with filtering this data in order to better utilise it (Keskin et al., 2021; Keiser, 2019; Gökçay, 2021).

Despite the fact that each organisation operates independently to obtain its own intelligence (Liu et al, 2014; Krishnan, 2021), the tasks of constantly tracking and detecting new sources of information as well as assimilating knowledge from various online sources are still a common challenge for all types of business (Guo, 2017). To achieve competitive advantage, managers are required to investigate the market, provide data analysis and marketing provisions through timely reports that can help the business to stay on top of the competition (Keskin et al., 2021).

Big data analytics (BDA), as a suite of technologies, have been reported to support the organisation's Competitive Intelligence (CI) throughout several sets of activities: Setting up source connections like social media channels, structuring the data, storing, integrating and providing a User Interface for data interpretation (Sharma et al., 2014). This convergence of BDA with the CI process is an area of interest for this study in order to investigate and dig further to assess the relationship between the two concepts. The research scope focuses on the real estate organisations in the UAE that implement BDA and also have constant marketing activities.

1.2.1 Research Context

The United Arab Emirates (UAE) is well known for its real estate development projects, especially in the Emirate of Dubai, where the government’s initiatives are keen to support the real estate market (CBRE report, 2020). By the end of 2020, Dubai’s delivered units were expected to reach almost 62,500 compared to the Emirate of Abu Dhabi, with just 8,500 expected units. As of 2020, there were 892 real estate agents (Land department, 2020) in Dubai, selling and renting properties and land in the UAE.

In 2008, the country faced a significant drop in real estate projects, with almost half of all construction projects in the UAE, worth around AED1.1 trillion (US$582 billion), being either put on hold or cancelled (Anon, 2015). Other industries in political, economic and social environments are contributing to the financial results and growth of the real estate industry. Competition is complex and requires multi-faceted considerations before any related decision-making.

In 2020, the pandemic caused by the novel coronavirus (COVID-19) have affected the market. The UAE, like other countries, have swiftly enacted a range of measures to control the spread of the disease. Moreover, the government and corporations were also moved to enact business continuity measures. Customer demand fell in in the first six months of 2020. For example, Dubai’s residential sector in the second quarter of 2020 sold only 5,233 units valued at AED9.06bn ($2.5bn), 40% down on the previous year (Khan, 2020).

Nevertheless, the real estate sector in Dubai has achieved remarkable progress over the years in global competitiveness indicators (Warrier, 2020). Dubai has become one of the world’s most attractive investment destinations, and the government was able to effectively enhance the position of the emirate worldwide, and attract investors by easing visa regulations, offering long-term visas and freehold properties in certain zones.

Moreover, Dubai has strongly addressed future plans to transform all sectors utilising advanced technology. Smart Dubai, the government’s office facilitating Dubai’s citywide smart transformation, has aligned with Property Finder group (Smart Dubai, 2020) to enhance the real estate sector in the region through smart technologies, to develop in-depth analysis, to formulate data-driven plans for the future, and to implement ground-breaking use cases.

Dubai has strongly supported data-driven culture in the government sector (Smart Dubai, 2020), and has been ranked, according to World Competitiveness Yearbook 2018, fifth globally in the use of BDA. The big data analytics summit is scheduled in February 2021 in Dubai, to discuss customer insights and business performance through advanced analytics and artificial intelligence. By 2022, 70% of the private sector in the UAE is expected to utilise big data and AI (Smart data, 2020).

BDA has gained interest intensely in UAE real estate, private and government sectors (Smart Dubai, 2020). Big data has helped organisations better understand their customer's needs to offer properties that best match their preferences. Thus, this interest has embarked on acquiring a greater market share of customers (Ayshwarya, 2021).

In fact, UAE businesses tend to constantly retain current customers as well as drive new customer acquisition like tourists and investors. The competitive strategy is increasingly deployed using big data to comprehend consumer moods and responses to products (Ayshwarya, 2021). The ability to exploit customers' feedback and sentiments has embraced personalisation in marketing campaigns (Rohma, 2021) to ensure awareness of the organisation's competitive advantage.

Nevertheless, the process of collecting market data and transforming it into a competitive intelligence tool in such a dynamic and innovative environment is considered one of biggest challenges for organisations in UAE (Afrah et. Al., 2019). Thus, an interest to explore elements of marketing activities towards competitive advantage using BDA in the above research context is an interest for this study.

1.3 Motivation

As a marketing consultant, co-founder and an academic researcher, this study has constituted a remarkable focal point in my life. Competitive intelligence activities have been part of my career for more than 20 years. This study has certainly added value to my career. Having knowledge of other research endeavours on the topic, reading results of various hypotheses and questions, becoming aware of the methodologies obtained and ideas for future research all greatly complement my conceptual and practical orientation.

Recent years have witnessed the emergence of artificial intelligence and advanced data management discourse in transitioning towards innovative and hi-tech marketing tools. This discourse has a technological basis, presenting the transition as an opportunity for market share growth through big data and its related analytics reporting.

As described by Ranjan and Foropon (2021), the integration between BDA and CI shall promote the value creation of the business, However, the problem with such integration is that it rises issues of prioritising and sequencing activities undertaken the process. Thus, exploring the systematic activities, how it runs and why is a great area of motivation to conduct this research

Yet researchers try to give grounds for this new managerial practice; my experience as a researcher reflects the term “double hermeneutic” by Giddens (1984). The topic places responsibility on myself to identify appropriate processes to engage stakeholders who are involved in the iterative design of the research context. In other words, interpreting a Socio-technological reality that has already been interpreted by practitioners and organisations in the field, and feeding these interpretations to the academic research to form a new knowledge and theory.

I understand now that the dialectical relationship between researcher and context has a mutual impact. Understanding a phenomenon requires making sense of it that fits within our own life context. My understanding becomes an interpretive act of integrating interviewee feedback into a meaningful whole.

My motivational factors are mostly intrinsic, and the inspiration I had during my research journey came from the ability I believed that I have to build and construct new things and my confidence in bringing these to fruition. Inspired by the self-determination theory of Ryan and Deci (2000), my lifestyle and extent of daily duties in my "to do" list all call for greater autonomy. Command of the subject studied has increased my confidence in researching, reading and writing. The big data topic is a competency which, as a marketer, I lacked knowledge of. Thus, my determination has increased every day, and the information I have acquired has inspired me to continue investigating further, even after completing my research project.

Informed by the literature (Boud et al., 1985; Kolb, 1984; Korthagen, 2001), I was motivated to be reflective in composing my research, in describing the process of learning while acquiring knowledge, and in discussing that which I could have done differently based on my experience (Bassot, 2016). According to Jasper (2013), a reflective approach will support me as researcher in establishing a baseline of lifelong learning and promotes both my personal and professional development.

The journey undertaken in this study was evidently not linear. Rather, it was recursive, as a researcher involving in repeated interviewing and interpretation of the collected data. My task was to unfold new facts that were not explicit for practitioners and researchers. My ultimate motivation were the findings of this research project.

Both my journey in acquiring this knowledge and in my professional role have benefited; each has its own utility and advantage in terms of direction taken, however, taken together, a solid and prolific tree shall be revealed.

1.4 Research Gap, Research Questions, and Aim and Objectives

BDA have several tools and platforms that have become available in the market in the last few years. Several industries are leveraging the power of BDA and have been extensively covered in the literature, i.e., supply chain, healthcare, marketing and customer experience, health insurance, information governance and logistics (Holmlund, et al., 2020; Hung, et al., 2020; Ho, et al., 2020; Mikalef, et al., 2020; Liu, et al., 2020; Sheng and Tsai, 2020).

As the use of big data nowadays largely contributes to the way of delivering competitive advantage to a business, strong alignment between competitive intelligence models and BDA is critical for business continuity and success.

Therefore, a range of recently published research literature on CI processes for collecting and analysing competitive information is reviewed to explore how organisations currently structure and manage the CI process. Although many papers highlight the new trend of digital marketing approaches, the existing CI models focus on non-digital components that are argued to be the most effective in achieving competitive advantage. Primarily, it is concerned with knowledge-sharing continuity through information management and feedback loop to help top management achieve effective decision-making (Allison, 2021; Van Den Berg et al., 2020; Adrian, 2017; Yin, 2018; Madureira et al., 2021).

While digital marketing aspects have been abundantly discussed in the literature, highlighting opportunities to achieve competitive advantage (Mikalef et al., 2019; Salleh and Janczewski, 2016; Sun et al., 2020; Kumar et al., 2020; Ranjan et al., 2022), the use of the massive amounts of digital information to improve the CI process has not yet been investigated to form a formal structure or a framework of the process (Holmlund, et al., 2020; Mikalef, et al., 2020).

But it is important to mention that a recent paper has investigated how organisations tend to contain BDA and what challenges might appear alongside the process (Ranjan and Foropon, 2021) Although the paper has focused on understanding the value of big data approach for a successful CI cycle, it did not cover socio-cultural aspects of the business environment that may contain influential factors, particularly external, which can affect the direction of the entire process. A comprehensive relationship between CI and BDA is yet to be explored, to allow researchers obtain a synthesised view of process components and relationship attributes.

This doctoral study aims to fill this gap by proposing an exploratory literature review and providing an artefact model of collecting, monitoring and analysing market data while implementing BDA. It intends to build on the existing relevant research works of necessary CI factors in a competitive environment (Chakraborti and Dey, 2019; Krishnan, 2021; Erevelles, et al., 2016; Chien et al., 2017; Merendino et al., 2018; Prescott, 2014) to construct a novel model that incorporates BDA in the existing competitive intelligence processes, seeking to improve and enhance decision-making outcomes.

Considering this study's research context (UAE) is a dynamic competitive environment (Khan, 2020), it was important to seek a model construct that contains interrelated phases and emphasises influential factors, internal and external.

Aside from talent management, skills and resources, the organisational agility and dynamic capabilities of the business culture, along with the knowledge sharing of the marketing mix, can all feed into a comprehensive model construct of both internal ability and external adaptation.

Therefore, among the existing reviewed CI models, Pellissier and Nenzhelele's (2013) model appeared to have necessary CI components to build upon into BDA utilisation, using the 61 process codes (Table 2) by Van Den Berg et al. (2020), which has helped embrace any potential factors that can affect the process.

The work fills the following two research gaps; Firstly, the literature lack of comprehensive relationship between CI and BDA. Secondly, from the methodological perspective, it will be novel to utilise DSR for developing a model within this context.

The research questions are:

1. What is the relationship between BDA and the CI process in a dynamic - competitive environment?

2. What are the benefits of combining BDA tools into the CI process?

Based on the existing literature review, and according to the theoretical gap of having no comprehensive guideline of the relationship between CI and BDA, aims and objectives were identified, as follows:

Aim:

The study aims to fill the theoretical gap and develop a novel artefact model encompassing CI process elements and adopting Big Data technology to facilitate an effective decision-making structure. The model shall build upon existing theories, extend the process to include all influential factors that may affect the sequence of the process, and provide a toolkit guide for CI practitioners. This aim entails the following objectives.

Objectives:

A. Conduct a thorough literature review to identify existing CI models.
B. Identify the common elements of CI process components through narrative extraction.
C. Construct the preliminary model integrating both BDA and CI together.
D. To elicit selected experts' perspectives and input following iterative cycles of interviews, and to validate model updates, as part of the DSR methodology.
E. Construct the final model approved by all participants.
F. Disseminate results of the new constructed model to practitioners.

Considering the attained DSR methodology, the research problem is as follows:

There does not exist a comprehensive model encompassing the entire CI process that is both formal, extending the existing models, and generic, that it contains all interrelated phases along with the external and internal influential factors *in the dynamic and challenging real estate industry in the UAE.*

1.5 Methodology

The design science research (DSR) approach is adopted to develop knowledge of a problem domain (Carstensen and Bernhard, 2019) by designing a novel artefact model that is capable of efficiently demonstrating the CI activities while utilizing big data technology. Hevner and Chatterjee (2010, p.5) define DSR as: "… a research paradigm that answers questions relevant to human problems via the creation of innovative artefacts, thereby contributing new knowledge to the body of scientific evidence".

Although Järvinen (2007) had strongly claimed that action research (AR) is similar to DSR in features and characteristics, stating that action research should indeed be considered as part of DSR, Iivari and Venable (2009) claimed it is not, and in particular, both AR and DSR are decisively dissimilar.

1.5.1 Justification of Selecting DSR

The selection of DSR for this study over other methodologies such as Action Research (AR) is due to the emphasis placed by DSR on upgrading present activities to new ones through innovative and novel artefacts (Carstensen and Bernhard, 2019), which is particularly suited to the task of analysing existing models of the CI process, assessing components, constructing a preliminary conceptual model, analysing and updating by interviewing participants and disseminating results while making it easy for practitioners to understand (Bider et al., 2020; Doyle et al., 2016).

While action research focuses on problematic situations (Davison et al. 2004) by identifying problems, gathers and interprets data, formulates future plans of actions based on evidences and lastly reflects on and evaluates results (Ince and Kitto, 2019), DSR focuses on creating a new reality, rather than explaining existing one or helping to make sense of it (Iivari and Venable, 2009), it works through constructing models, methods or instantiations that help in creating innovative and new artefacts (Hevner et al., 2004).

Also, while grounded theory appears to have similar approaches in terms of data collection and communication with participants, though, it is not a problem centred study and does not concern with the design, development and subsequent evaluation of artefacts. Therefore, DSR is deemed appropriate because of the type of problem this thesis is concerned with. The characteristic of the problem considers practitioners, technology and business practice that is not evident yet how it all manipulates the process to best achieve a competitive advantage for the business and make up the artefact.

The solution to the problem still depends on the practitioner’s managerial and technological abilities to perform competitive decisions that serves consumer demand and satisfaction.

Since this research outcomes aim to provide a new design for the competitive intelligence process for organisations that are in favour of BDA implementation, DSR helps in achieving this aim by producing rigorous research into a new process model of IT artefacts that are acceptable for the information system (IS) community (Morana et al., 2018).

The artefact related to this research is a new model, a Comprehensive Competitive Intelligence Proses- Big Data Analytics Based Model (CCIP-BDABM). The organisational context associated with this research is the real estate industry in UAE, which are in favour of BDA utilisation that the marketing department particularly uses. Hence, the research problem is that there does not exist a comprehensive model encompassing the entire CI process that is both formal and generic; the DSR is considered the most appropriate choice, which can focus on the design and development and subsequent evaluation of CCIP-BDABM.

1.5.2 DSR Process

Hevner (2007) provided three DSR cycles: relevance, design, and the rigor cycle. The first cycle investigates requirements, followed by building and evaluating the designed artefacts, then, finally, a research contribution which is grounded in a knowledge base. In fact, Bider et al (2020) emphasises innovations through the DSR cycle, ensuring the necessity and importance of creating knowledge throughout artefacts creation.

Drechsler and Hevner (2016) suggested a fourth cycle, the change and impact cycle, which links the DSR project to the wider environmental context.

The process iteration created in Hevner's model has been utilised by researchers (Sein et al., 2011; Vaishnavi et al., 2013). The papers prove that iterative cycles between research design activities allow feedback from one phase to go back to an earlier phase for modifications and additions, which would eventually help in designing a better result.

Further approaches towards the DSR process such as the evidenced-based design cycle (Wieringa and Morali., 2012; winter, 2013) look for scientific explanations by investigating generic technologies first, followed by customised solutions that can be implemented in organisational operation. Another approach utilises DSR by distinguishing differences between real world and abstract factors (Gregor, 2020; Lee et al., 2011). The distinction between instance and abstract, theoretical and practical, classes of problems and specific problems is called the abstraction cycle.

Another process model for producing and presenting Information Systems Research was presented by Peffers et al., (2006). The Design Science Research Process (DSRP) follows six steps: (1) problem identification, (2) objectives of a solutions, (3) design and development, (4) demonstration, (5) evaluation, (6) communication. The objectives of this (DSRP) approach are to be consistent with existing literature, provide a comprehensive process model and evaluate DSR through a mental model.

In comparison with Hevner et al. (2007) cycles, it is clear that *relevance* is demonstrated in *problem identification* and *objectives of solutions*. The *iterative process* and *artefact* are the same in the third step of *design*. *Evaluation* and *communication* are each demonstrated in both models. The fourth step in Peffer's model of *demonstration* embodies an eminent feature, where researchers find suitable context and use artefacts to solve problems.

Within literature, artefact development was conducted following a systemic DSR approach and using Causal Loop Diagramming (CLD) within the education subject area (Heathcote et al., 2020). Therefore, although DSR is predominantly an information systems artefact development methodology, it has been adopted in a few other disciplines and applications (i.e., Heathcote et al., 2020; Montasari, 2016) and it is argued that the approach introduced by Peffers et al. (2006) is more comprehensive and offers a graphical representation (Montasari, 2016). Figure (1) illustrates DSRP applied to this study.

Peffers et al's (2006) DSRP model has been selected as it provides a graphical representation of the conceptual process for both carrying out and presenting the DSR. The conclusion of the graphical element of the process model was deemed as being valuable in offering a manageable data strategy following establishment of the required artefact. Since the focus of this study being the problem that there does not exist a comprehensive CI and BDA model, the artefact result aims to develop a new model; a Comprehensive Competitive Intelligence Process-BDA Based Model (CCIP-BDABM), which comprises all steps of conducting competitive intelligence while utilising BDA technology. The organisational context is real estate firms in the UAE who practice BDA.

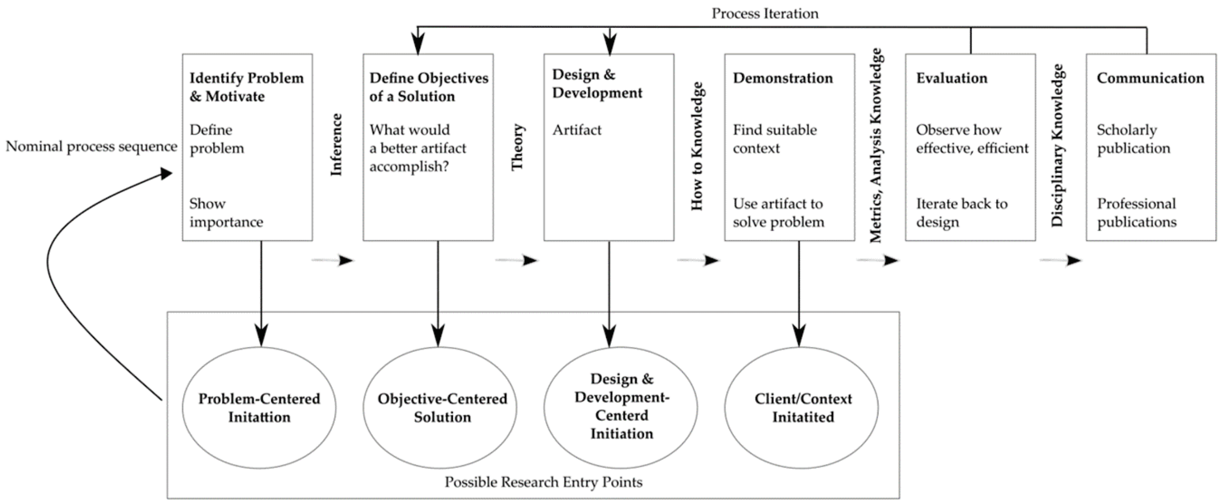

Figure 1 The DSRP model (Heathcote et al., 2020), and after Peffers et al. (2006)

1.5.3 Method

The quantitative approach is typically followed when using DSR in research (Baur, 2017; Bell et al, 2019; Mramba, 2016; Mettler, 2011). However, since this study is concerned with collecting experiences of running competitive intelligence and BDA and understanding different perspectives that involve in generating words (Merriam, 2009) of how this process works rather measuring numbers related to this operation, this study follows a qualitative approach that has been similarly adopted in other similar studies as well (Grenha, et al., 2017; Montasari, 2016; Seng, 2019).

A qualitative approach was employed through semi-structured interviews for data collection to secure rich descriptions supporting the purpose of the research. Interviews helped the researcher to gain an in-depth understanding of the complexity of the phenomena (Creswell, 2014) and to establish the meaning of experiences from the perspective of those involved (Merriam, 2009). This research approached experts from both corporate and academic settings. They are all experts in the field of marketing and big data solutions. Experts from corporate settings were selected from medium to large-sized real estate corporations in the UAE; they are decision-makers concerning marketing and big data solutions. Academic participants are working in universities in UAE, and all are specialised in big data and advanced technology solutions.

The justification behind choosing two different settings of interviewee context is that the "standard pool of knowledge" differs between academics and practitioners (Southgate, 2006); which could position academics in a more challenging role to open the dialogue with practitioners. Moreover, academics spend twice the time on research activities than non-academics do (Chaker et al., 2020), which could create a gap between theory and current practice. Browne and Yoder (2018) call for the urgency in connecting academics and practitioner knowledge to avoid expensive mistakes (Browne and Yoder, 2018).

1.5.3.1 Research Philosophy

The study has adopted an ontological philosophy of constructivism; the researcher assumes that reality is found intersubjectively via meanings and understandings, developed socially and experimentally (Merriam, 2009). Unlike objectivism philosophy that views knowledge as some entity existing independent of the mind of individuals (Piaget, 1977), constructivism philosophy believes that truth is created by experiences of these individuals (Rosa et al., 2020). So, since the research strategy of this study is approached on the basis of experiences of experts, thus constructivism is justified as best philosophy applied for this study.

Therefore, a philosophical, epistemological approach of interpretivism has been followed, allowing the study to look for in-depth information in individual intentionality (Husserl, 2012) rather than hypothesis development (Silva, 2021). The interpretivism approach supports the researcher in collecting unique life experiences from participated experts working in both CI and BDA fields and accordingly provides an eminent picture of reality by which our mental small world representation or model of reality is constructed (Maitland and Sammartino, 2015).

1.5.3.2 Data Collection

Through inductive reasoning, the study began with literature mining for the latest proposed CI process models, aiming to advance an abstract generalisation (Heit and Hayes, 2005) and statements. Design Science Research (Hevner et al, 2004; Peffers et al, 2006) has been selected as a main strategy for this research project.

And since the data was collected qualitatively from the experiences of related community experts, the data intensity is very high; the generated knowledge and findings are achieved by developing an artefact that addresses important and relevant problems of the existing competitive intelligence process in the real-life practice.

In the vast majority of research undertaken, it is not possible to collect data from every member of a population. Therefore, a proportion is recruited to represent the entire population (Ames et al., 2019). It was necessary to ask which and how many individuals will represent the population. The study focus was to develop a global understanding of the phenomenon of CI process and BDA employment, including similarities and differences across different settings (Ames et al., 2019), and the DSR methodology has embraced the understandings of these particular settings, through conducting interviews that keep iterating until the generated knowledge and results are confirmed by all participants.

Accordingly, the study has applied purposive sample selection (Patton, 1990), which will provide the most information on the subject of interest (Guarte and Barrios, 2006). Since the methodology aims to produce a novel model extracted from the field of experiences, experts of CI and BDA community have been purposely approached (Suen et al., 2014). A total of 8 experts, practitioners and academics, were selected to conduct a total number of 27 iterative interviews. The selection of experts was based on their level of experience that matches with the intensity of the phenomenon under investigation.

The qualitative data analysis software Nvivo12 was used to support manual qualitative analysis. The coding has helped in managing and analysing interview results. Also, as part of the study, a gap analysis between feedback from practitioners and academics has been conducted to compare between knowledge and other aspects concerning implementing BDA towards achieving CI.

1.5.3.3 Research mental model

This study aims to investigate BDA intervention variables throughout the competitive intelligence process as best corporate practices towards enhancing business competitive performance in the real estate industry. To achieve this goal, six activities of DSRP are adopted throughout the course of the study (Peffers et al., 2006), to build and evaluate the proposed model (CCIP-BDABM).

First Activity: Problem Identification

As the first activity plays an important role in implementing the conceptual process and mental model to present the research and evaluate the outputs, defining the research problem shall be achieved by an exploratory literature review to verify the main variables of the competitive intelligence process. The research focus is to develop a comprehensive process of competitive intelligence that can directly affect business performance.

The process phases thoroughly integrate factors that are relevant to BDA implementation and the decision-making structure. Current literature provides a detailed description of the CI process, which helps guide the problem context. How can BDA be adapted within the CI process? What changes in the decision-making structure? Is the process cycle time affected? Figure (2) demonstrates the problem context for this research project.

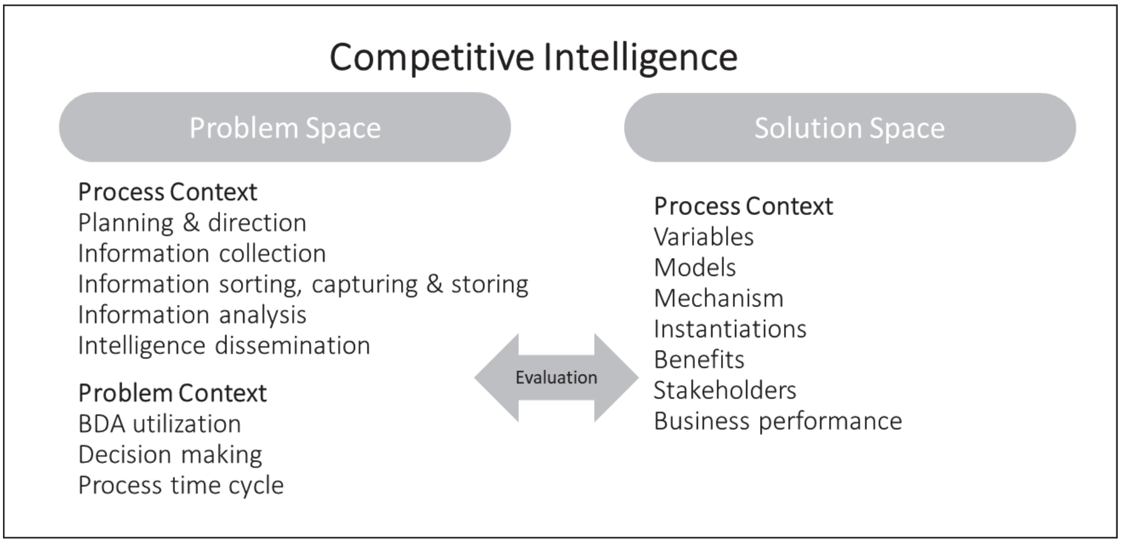

Figure 2 Problem context of this study

Formulating the competitive intelligence process while implementing BDA is the problem space aiming to construct a model solution that helps businesses performing higher competitive advantage. The exploratory literature review will provide a profound knowledge addressing the research problem through assessing components of existing models related to the research focus.

Second Activity: Objectives of a Solution

As it is essential to keep the DSR project consistent with prior research (Peffers et al., 2020) and to derive objectives rationally from the problem specification, it was important to build on knowledge through existing literature review and define solution objectives to provide a nominal efficacy process that facilitates identical results of business-competitive performance, if not greater, to decision-makers.

Third Activity: Design and Development

Create an artefact that solves the problem. Design of CI and BDA model, to be used in the marketing domain that is interested in maintaining competitive advantage. The model construction shall follow mandatory ingredients (Chouder and Chalal, 2014; Yin, 2018):

1. The process must achieve actionable intelligence
2. Credible and trustworthy

3. Clear definition/s of project community
4. Adapt the knowledge and learning factors

Having set the basic structure of the new model, it shall support the design and development activity during the assessment of existing models in the literature review, with an extensive highlight of project community and decision makers, to achieve usability, utility and rigor, as set out by Beebe and Clark (2005). Accordingly, the Comprehensive Competitive Intelligence Process- BDA Based Model (CCIP-BDABM) was proposed.

Fourth Activity: Demonstration

After attaining theoretical knowledge, resources are required for the design and development of artefacts. The real estate firms and the academic universities in the UAE were approached to select the list of interviewees. Eight participants were assigned for this study, to evaluate and motivate design choices during the model construction process.

However, before the full-scale interviews, in this DSRP activity, the researcher is required to apply the artefact in an appropriate environment, such as "experimentation" or a "case study" to solve the stated problem (Hevner and Chatterjee, 2010; Peffers et al., 2006), and seeking for resources of effective knowledge about the artefact application. In order to assess how CCIP-BDABM addresses the stated problem, several meetings were needed with two industry experts; one working at a managerial level in a real estate company in UAE, and the second is an assistant professor working in a university in UAE. The meetings were to discuss and apply the CCIP-BDABM to their level of expertise, to ensure the validity of CI process phases in the work field. Moreover, pilot interviews were also conducted with a further two managers in the fields of marketing, competitive intelligence, and BDA to verify questions before it is finalised, which will support in avoiding confusion arising during the research interviews. Accordingly, the semi-structural questionnaire was formulated, following the cycles of the competitive intelligence process from beginning to end.

The rationale for selecting different candidates is to ensure the applicability of the CCIP-BDABM to the participants' settings, including practice and academics, and to determine whether any alteration is needed for the design and development phase. The demonstration activity will enable any shortcomings to be addressed prior to the submission of the model to the research participants for formal evaluation.

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Fifth Activity: Evaluation

In this phase, it is necessary to observe and measure how effective the artefact supports a solution to the stated problem. Solution objectives in activity 2 were compared to actually observed results demonstrated in activity 4 (Peffers et al., 2006). During this activity, and if it became evident that the artefact required additional development, the researcher could decide to move back to activity 3.

During the Evaluation Phase, the CCIP-BDABM will be submitted to real estate marketing practitioners and academic experts in the BDA and business domains to which the model has relevance. The evaluations will compare the model's application and effectiveness with the necessary elements for CCIP-BDABM (discussed in chapter 2). Such an approach aims to enable the researcher to acquire insightful and reliable feedback on the effectiveness of the CCIP-BDABM in the current field of practice.

Sixth Activity: Communication

As the final activity, the researcher communicates the research problem and its implications for the research and the related audience, the artefact, its utility and novelty, and the robustness of its design (Peffers et al., 2006). Certainly, this activity requires knowledge of the disciplinary culture.

1.6 Contribution to Professional Practice

The real estate industry faces problems of fierce competition in the UAE due to a variety of political, economic, touristic and social aspects (Anon, 2020). The findings would benefit practitioners who use or intend to apply BDA as a supporting tool to achieve a successful competitive advantage. The research significance of identifying best practices of the CI process and BDA implementation will help organisations to identify their own appropriate sources and tools of BDA to be utilised within a strategical and operational level of CI. From the decision-making perspective, the study provides guidance on managing and linking CI and BDA operations to best achieve business and marketing objectives.

Existing theories support businesses towards operating competitive intelligence process. However, since UAE's private sector utilisation of BDA is expected to reach 70% by 2022 (Smart data, 2020), this study has provided the actually needed guide, of how to run competitive intelligence while geared by BDA.

1.7 Contribution to Knowledge

The subject of competitive intelligence is a constant area of investigation for researchers (Chakraborti and Dey, 2019). However, the scope of the CI process while implementing BDA is a developing subject (Calof and Dishman, 2002; Boyd and Crawford, 2012; Theriot, 2014; Mikalef et al., 2019)

). The use of DSR in this study, creating a new innovative model combining CI and BDA makes a novel and significant contribution to the theory. The research builds on existing models in the literature in order to assess the performance of elements that can be constructed in a new and novel one.

1.8 Ethical Considerations

This study looks at participants from corporate and academic settings in the UAE. All participants are experts in the field related to the research topic. Therefore, it is important to mention that the researcher is not a line manager nor works with any of the respondents. In order to conduct this research, the researcher followed the research ethics code and procedures of the University of Northampton dated October 2018. An ethics application was submitted to the research ethics committee at the

University of Northampton, and approval received with the reference number ETH2021-0017. Considering any positionality concerns, there is no insider researcher in the proposed study context.

Full ethical consideration and guidance is strictly followed, and as highlighted above, a full approval from the University research ethics community has been sought. In order to increase research credibility (Leavy, 2017), informed consent was obtained in all cases, participants have not been pressurised and their participation has been voluntary, also offering a reasonable right to withdraw from the process.

1.9 Thesis Structure

Chapter 1, Introduction to the Research. It explains the background, context, research gap, questions, aims and objectives, methodology, research contribution and ethical consideration.

Chapter 2, Literature Review. provides a general overview of competitive intelligence and related sub-topics that can affect the decision-making within the CI process, followed by a critical review of the existing CI models. The chapter also covers big data and BDA technological inputs towards enhancing business performance and discusses the organisational intention towards investing in big data. Finally, the model fundamentals and the necessary elements for the proposed model are identified from the key contributions of the prevailing models.

Chapter 3, Methodology. This chapter presents and justify the research methodology adopted to develop the conceptual solutions (the proposed model). Discussion of research philosophy, approach, techniques, strategy, sampling and method are all detailed in this chapter.

Chapter 4, Findings and Discussion. It provides details of findings based from practitioners and academics interview results. Followed by gap analysis, and finally critical discussion.

Chapter 5, Conclusion. This chapter concludes the findings by answering the research questions and checking achievement upon research aims, objectives and research problems. Next is research contribution, future work and limitations.

1.10 Chapter Summary

This chapter has introduced the study's main pillars of aims and objectives, context, motivation, contribution, and methodology. The philosophical approach is constructivism interpretivism with inductive reasoning utilising semi-structured interviews. The study addressed the issue of no existing model explaining CI process while utilising BDA in the literature, and thus DSR strategy is approached to construct a novel artefact model which can contribute to knowledge and practice. Next Chapter outlines the comprehensive literature review that was undertaken as part of this doctoral study.

Chapter 2 – Literature Review

2.1 Preamble

Researchers have investigated areas that bring the CI term from being intuitive into an evident strategical plan that integrates both knowledge management and decision-making towards business growth (Fleisher, 2004). The information technology revolution has provided organisations with competitive intelligence tools to outperform their rivals. It has resulted in collecting a wealth of data to support business performance. However, competition is increasingly fierce, resulting in competitive intelligence tools seeking to have more advanced and technological facets that can provide analytics involving large datasets of market information.

To that end, this chapter reviews the existing literature, which underpins the thesis topic of competitive intelligence process in the era of big data analytics. It starts by exploring elements related to the competitive intelligence process: competitive environment, decision-making and models, dynamic capability, organisational agility and knowledge. Next, it discusses the technological intervention of BDA and the organisational intention toward investing in big data.

2.2 Literature Review Protocol

An extensive exploratory review undertook the competitive intelligence process and the decision-making models that relate to intelligence inputs and outputs. CI-induced cycles are a sequential process in that each cycle is dependent on the previous one, and all factors are mutually involved. Many studies have covered the CI process in the literature. Cycles and factors affecting CI have varied between studies. To better understand the process, cycles have been reviewed and assessed based on decision-making efficiency, harmony, connectivity, and CI results sufficiency. The decision-making structure and models were also reviewed, and accordingly, a conceptual decision-making model relating to the CI process have been produced.

While attempting to embrace a comprehensive CI process in the era of BDA technology, other related topics are considered essential for the formation of the process. The researcher had to explore knowledge, BDA reports and CI environments in order to help clearly define the research problem. Without intending to offer any conclusive solutions (Saunders et al., 2012), this study explored publication trends in organisational competitive advantage studies, and factors affecting the formation of organisations' readiness to fiercely compete in the market.

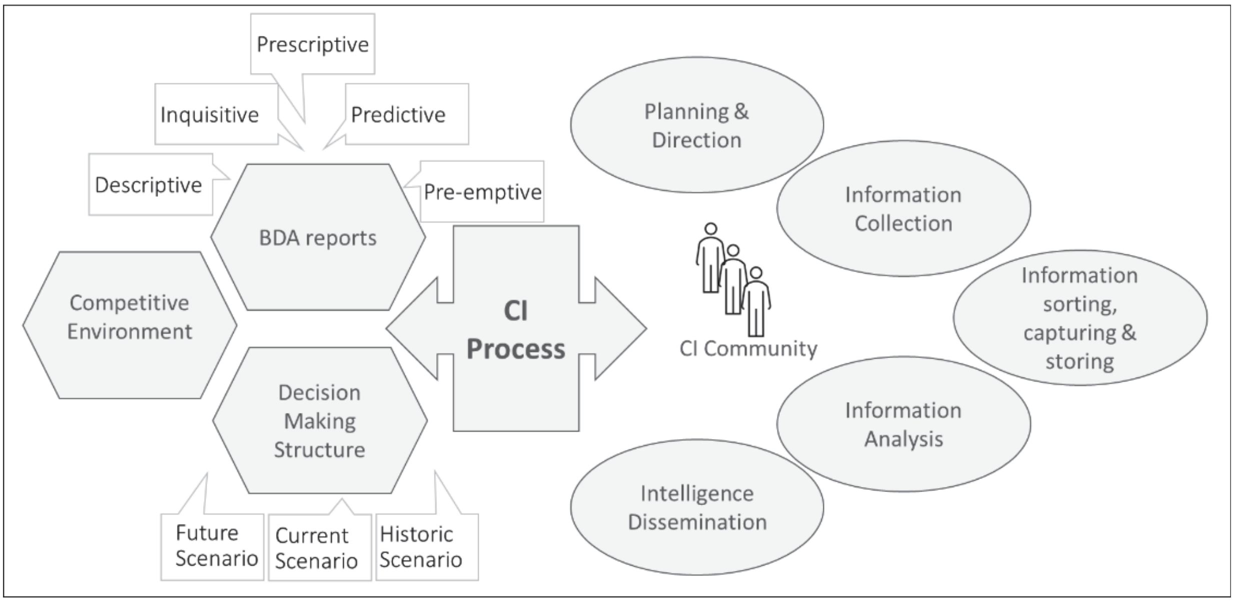

Figure 3 Concept map of this study

The concept map (Figure 3) shows the necessary components that will be used in the research design and methodology to produce a new model. The map shows the main activity, CI, along with related intervention factors that can affect the efficiency of the process.

The literature search was mainly conducted using Nelson in the first instance, Northampton University's Electronic Library Search ONline, followed by Google Scholar and EThOS, the UK's national thesis service. The keywords are based on the research topic of CI and BDA. All articles were peer-reviewed and in most cases, are recently published articles, though important theories identified in older studies that can contribute to knowledge are included.

2.3 Competitive Intelligence (CI)

Several definitions of competitive intelligence were found in the literature. Fleisher and Wright (2009) pointed out that CI definitions are concurrent in terms of objectives, but differences in terms of semantics and emphasis are presented. According to Brody (2008), the variety of definitions is attributable to constantly changing business environments, making CI a dynamic tool in tracking competitors' behaviours.

In 1988, Gilad and Gilad have recognised Competitive Intelligence as the selection, collection, interpretation, and distribution of public data or information of strategic importance to the decision-making process (Gilad and Gilad, 1988). The definition pillar stands for two main themes: strategic planning and decision-making. A more recent approach has updated the definition of CI as: "the collection, analysis, interpretation, and dissemination of high-value information about strategic areas, which is transmitted at the right time to decision-makers" (López-Robles et al., 2020). The extant literature has largely overlooked competitive intelligence through a series of data processing contains decision-making aspects. The latest definition of CI by Madureira et al. (2021) provides a comprehensive overview of the process: "CI is the process and forward-looking practices used in producing knowledge about the competitive environment to improve organisational performance."

An increasing number of recent studies on competitive intelligence have been published to highlight conditioned actionable insights towards achieving CI. Tawodzera (2018) claimed CI as a systematic and ethical tool that provides actionable intelligence about the competitive environment in order to support decision-makers. The author recognised information as intelligence and described it as an ethical activity, which had echoed with what Vriens (2004) stressed on concerning the necessity of excluding any act of espionage, and keeping the context portrayed as an ethical and systematic approach only. More assertive approaches in defining CI have stated that competitive intelligence is a timely mannered organisational approach to collect product-firm-market intelligence using a variety of internal and external sources of information (Kumar et al., 2020, p.206).

The literature contends that CI analysis approaches are dissimilar (Krishnan et al., 2021; Moore, 2002; Michaeli, 2010). Each approach presents the purpose and the level of analysis; descriptive, explanatory, interpretive and estimative (Tawodzera, 2018). Noting these differences in the CI analysis approach, one question critically arises: is it affirmative that CI will achieve its target using any of these approaches or is there a room for uncertainty using a specific approach? Delving further into the literature on how best to achieved desired CI performance, it appears that competitive intelligence had been deployed mostly in the operational level and have not utilised the digital capability to its full potential (Holmlund, et al., 2020). This is due to the lack of clear formal structure for CI along with the use of BDA in building organisational competitive advantage (Ranjan and Foropon, 2021; Ranjan et al., 2022; Mikalef et al., 2019)

More Over, the phrase Talent or Talent management (TM) is raised in some academic papers (Krishnan et al., 2021; Ross, 2013; Fegley, 2006; Moore, 2002; Cappelli and Keller, 2014). It claims that the competency level of CI specialist is the first criterion for the success of CI analysis. Hence, more researchers have begun investigating skills of CI specialists, which stems from the valuable competencies that are able to enhance CI performance.

Tawodzera (2018) categorised CI specialists into levels, the highest of skills and competencies is called Grand Master. This particular category - Grand Master- is able to provide estimative analysis, which in turn will produce insights of significant impact on business performance. On the contrary, Moore (2002, p.6) deemed it to be the other way around; stating that estimative analysis, if approached, is a key success provider for any specialist who seeks information that can judge the future.

Talent management consists of systematic activities and commitments that seek a sustainable competitive advantage (Gallardo-Gallardo et al., 2020). This set of activities or competencies are crucial to business success and should be applied strategically (Cappelli and Keller, 2014). Charan (2008, p.41) described talented leaders in his book as “folks who you would walk through fire for”. This is because of the unique competencies they have, like the ability to communicate and articulate vision, adapt quickly to market changes and most importantly, align teams together.

Despite the abundant coverage of talent management as a fundamental discipline in the business management field (Thunnissen and Eva, 2017; Rego, 2017; De Boeck et al., 2018), it is critiqued on the other side that the organisational context was not part of assessing TM effectiveness (Collings et al., 2019), rather, it is mainly discussed as a rational and instrumental process in managing talents. Therefore, Gallardo-Gallardo et al. (2020) stressed the importance of studying each organisation’s operational setting as a contextual talent pool that is able to define desired competencies according to its own business objectives.

2.4 CI Environment

It has long been recognised that competitive advantage is a strategy of value-creation to differentiate business from other competitors within the shared environment (Barney, 1991). Through either the capability-based view (CBV) or the resource-based view (RBC) of competitive advantage approaches, strategy is required to utilise environmental resources in order to sustain competitive advantage in the market (Kumar et al., 2020). In fact, it is imperative in some competitive environments to construct multiple and diversified strategies (Lapersonne, 2013) for the constant changes in the environmental resources, which requires swift adaptation and configuration.

Organisations follow different approaches towards the competitive environment: innovation and imitation, and each expects two speeds: fast and slow (Pacheco, 2010). Although most scholars have investigated the competitive environment as a turbulent marketplace with probable disruptive changes (Mao et al., 2015; Dilanian and Howard, 2020), Lapersonne (2013) put together three classifications of competitive environment: stable, dynamic, and high velocity. On the other hand, the theoretical framework of environmental resources (Ko et al., 2017; Alvarez and Busenitz, 2001) can predict the organisation's competitive advantage based on its resources. The VRIN framework (Barney, 1991) calls for valuable, rare, inimitable and not substitutable resources.

Components of the CI environment have varied in the literature. Degerstedt (2015, p.34) listed components of the competitive environment as: competitors’ annual reports, customer feedback, industry experts, regulations, tradeshows activities, photos, movies and sounds. The recent conventional approach has restricted the components to technological aspects, market opportunities and competitors' threats (Iwu-James et al., 2020).

A more comprehensive approach by Sharp (2009, p.38) appears more adequate to support the scope of this research project. It consists of demographics, economy, other industries, technology, distributors, customers, substitutes, suppliers, government and industry regulators, prospects, culture, and competitors (Table 1). The components appear sufficient to cover all factors surrounding organisational competitive environment. However, it is suggested to add one additional factor of "unexpected circumstances" for any additional source of information that is not listed, allowing decision-makers to adapt swiftly to changes (Maungwa and Fourie, 2018; Köseoglu et al., 2019; Kumar et al., 2020; Sewdass, 2012).

Table 1 Competitive environment components, adapted from Sharp (2009)

Competitive Environment			
Demographics	Economy	Other Industries	Technology
Customers	Substitutes	Suppliers	Regulations
Competitors	Culture	Distributors	Prospects

Despite the fact that competitive environment components have been covered theoretically, it was a point of interest from the organisational industrial perspective too (Krishnan et al., 2021). Albert Humphrey, a researcher at Stanford Research Institute (1960 – 1970), while analysing why corporate planning fails, formed the well-known marketing theory of SWOT analysis. Two factors should be analysed that are conducive to business development and competitive advantage: internal analysis of an organisation's strength and weaknesses, and external analysis covering any threats and opportunities in the environment.

To date, SWOT analysis is commonly used by practitioners aiming to achieve optimal market share and high sales that would satisfy shareholders (Intyas and Primyastanto, 2020). However, on the other hand, Porter (2008, p.25) claims that "managers define competition too narrowly". Despite the fact that organisational profitability drivers are similar, it has to go beyond competitors only. Porter provided five forces that shape this environment: established rivals, savvy customers, powerful suppliers, aspiring entrants and substitute offerings. The features of these forces have a powerful insight to elevate organisational performance. More so, with carefully analysis of these forces, the organisation can evolve its competitive advantage and swiftly demonstrate a larger market share.

It is important to highlight here that the theory of hypercompetitive environments (Lapersonne, 2013), which characterises the environment by high-velocity and a high level of rivalry, it is possible that Porter's five forces (Porter, 2008) are difficult to be applied in such environments. In fact, Porter's positioning approach constrains an organisation's competitive advantage to the valuable value chain. An organisation working inside-out, based on the resource-based theory, shall attain a challenging strategy implication, particularly problematic in adapting environment changes. Hereafter, it is vital to assign a strategist who can understand market attributes, identify business positioning and, most importantly, set a strategy that is able to solve constraints and move forward growth and profitability (Intyas and Primyastanto, 2020).

Lumpkin and Dess (2001) claim that successful organisations have an explicit relationship between strategy, organisational structure and environment. Heterogeneities in environmental changes place a burden on the strategy's wisdom and innovation, which can create a structural glitch (Allison et al., 2020; Miller and Friesen, 1983). Moreover, external environmental factors have a direct influence on internal organisational structures like administrative efficiency and operational efficiency (Pang et al., 2014). Therefore, the organisational flexibility towards environmental rapid changes is crucial to sustain a robust business structure and control operational efficiency (Liu et al., 2018). Following this statement, two theories are found related to organisational flexibility in the competitive environment: Organisational Agility (OA) and Dynamic Capabilities (DC).

2.4.1 Organisational Agility

The term refers to the sensing and responding abilities (Allison, 2021; Overby et al, 2006) of detecting activities and changes in the business environment and, at the same time, gaining information that can help to respond to these changes while aiming to elaborate the organisation’s competitive advantage (Bhandari et al., 2020; Mathiyakalan et al., 2005; Ganguly et al., 2009; Barreto, 2010; Liu et al., 2013).

Both knowledge and internal mechanisms can guide OA and achieve the desired performance (Allison, 2021; Mao et al., 2015). Similarly, Nonaka (2009) believed in knowledge but together with information. Having two indicators may have limitations, such as performance level, and conditional relationship towards the result. For example, Liu et al. (2010) surveyed 117 organisations about the driving internal mechanism of proactive corporate environmental behaviours. It was found that the effective reactions of a company’s stakeholders will guide the internal mechanism and improve the organisation’s environmental performance. Empirical evidence is subsequently needed to test stakeholder’s relationship with knowledge, to generalise the positive impact on OA.

Further research in the organisational agility area has highlighted organisational culture as the main stimulant of OA (Felipe et al., 2017). The culture controls the information system, which in turn will operate in flexibilities towards environmental changes. The statement appears theoretically sufficient; however, organisational culture pillars might vary between organisations in the field. Porter’s (1992) study (also discussed in Sabri (2019) supports the notion of a culture who relies solely on specific measure like financial or tangible measures, it will sacrifice long-term value creation for short-term benefits.

Wernerfelt (1984) summarised that a strategy is required for the internal process while utilising external market resources. The author believed that OA would perform as a market intelligence analysis, creating synergy between all external resources of the organisation’s competitive environment, in order to achieve notable organisational performance with favourable competitive edge.

A recent study comprehends OA in terms of achieving a successful competitive advantage (Allison, 2021). It claims that despite the need for resources and competencies to proactively adapt to situational changes, there is no definitive method to be used. It relies on how much a decision-maker uses evidence-based methods, where strategic plans fit into the organisation's benefit.

2.4.2 Dynamic Capabilities

Perhaps most, if not all, optimal business objectives are to sustain profitability through any market circumstances (Keskin, 2021). Teece et al. (1997) proposed the appropriability regimes for business sustainability, which are based on product replicability and intellectual property rights. Two dominants define how weak, moderate or strong the business is. The strong positioning requires strong competitive advantage; either long- or short-termed. An organisation's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments (Linden and Teece, 2018) is what sustains competitive advantage, and is referred to as dynamic capabilities.

A perfect environment doesn't exist (Kumar, 2020) and disruptive changes in the environment are expected, and because VRIN of resources is greatly needed to maintain competitive advantage, the dynamic capabilities theory proposes timely responsiveness, flexible production of innovation and managed capabilities (Teece et al., 1997). Moreover, some papers in the literature have reported that the dynamic capability theory allows businesses to effectively coordinate internal and external competencies (Mikalef et al., 2019; Slaouti, 2021; Wu et al., 2016; Barreto, 2010). One of the main concerns of generating competitive advantage from DC arises from the vague definition of the competitive environment. Some studies in this area appear to be concerned with the decrement value of DC in some competitive environment circumstances (Slaouti, 2021). Although Zhang et al., (2019, p. 1116) claims that DC can "sustain the competitive advantage in a rapidly changing environment", some scholars argue the validity of the existing systematic relationship of DC and competitive advantage. Some reasons are attributable to the commonality nature in the environment (Eisenhardt and Martin, 2000) or for the unsolid plans of business leaders (Fainshmidt et al., 2019), both of which demonstrate providing temporary competitive advantage only.

A business strategy to enhance dynamic capabilities should concern with alternatives and choices. Linden and Teece (2018) explored DC for decision-makers attaining competitive advantage while exploiting the existing and new entry market. The authors concluded that despite decision-makers being unable to predict, they must articulate a strategy of choice, commitment, and search. On the other hand, some studies claim that decision-makers can correctly predict if they manage internal and external resources to build on the most suitable strategy for a competitive environment (Allison, 2021; Ullah, 2021; Lapersonne, 2013).

Four essentials for the organisational capabilities are reported to provide precautions for the business (Slaouti, 2021): environment, complexity, risk and a maintained business model. According to the organisation's situation and objectives, decision-makers can choose the most appropriate approach to adjust dynamic capability for the business. Tidd and Tidd (2006) confirm three factors that determine the strategic nature of the organisation. First is the position of core competencies performed by the current endowment of technology and the relationship with customers and suppliers. Second is the path that refers to the organisation’s strategic direction and technological trajectory. The third is the process of the organisation’s culture while behaving to work routines.

2.5 Decision-Making

A bibliometric analysis by López-Robles et al. (2019) revealed the most common themes of CI in studies between the years 1984 to 2017. Remarkably, “decision-making support” was the main theme at the end of the study period, indicating how vital decision-making is to the CI process and performance.

Although there is consensus in the literature with respect to naming all who work for CI as a CI community, there is a conflict with respect to naming and selecting the main decision-maker among them. According to Miller (2000), the CI community comprises of top management (decision-makers), line manager and CI staff. On the other hand, Chen (1995) claims that marketing managers are the core of CI and hence they are the decision-makers. Tawodzera (2018) states that the CI community comprises of CI director (decision-maker), CI manager and CI analyst/staff.

The systematic generation of decision-makers is a vital organisational function. In a recent interview with John Troxell, a senior US military officer, while being questioned about his direct supervisor’s characteristics towards achieving maximum competitive advantage, he said: “nothing kept him awake at night; he kept others awake. I suppose I was one of those people!” (Arpi and Matthew, 2020).

Despite the debate on whether effective CI decision-makers are born or made, the literature acknowledges that an organisation’s performance depends on decision-making as one of several factors affecting organisational performance (Calof et al., 2018; Markovich et al., 2019). Pellissier and Kruger (2011) reported that extracting meaningful insights can be a major obstacle for decision-makers; this is due to lack of information reliability and accuracy. Also, Kumar et al. (2020) referred to the difficulty of extracting information from external environmental resources, due to the inability to draw inferences derived from contradicting information. Moreover, the personal intelligence of the decision-maker is crucial with respect to how and when skills, knowledge and competence are demonstrated effectively (Fleisher and Craig, 2009). It is important to concede that the decision-maker is an individual - part of society - with the assumption that people are not necessarily intelligent in all areas. Nevertheless, it is possible to expect and achieve higher competencies when talented individuals are exposed to appropriate stimulating experiences and practices (Ozturk and Debelak, 2008).

In this regard, talent management of a specialist’s competencies and hiring a grand master who is able to provide estimative analysis could constitute a theoretical solution. It seems that organisations look for eminent competencies which enable decision-makers in providing actionable intelligence of significant impact for the organisation’s competitive intelligence. In fact, it appears that the multi-intelligence theory by Garners (1990) can tap into these intelligence types in order to increase the effectiveness of decision-making.

The eight types in Garner’s intelligence model (Figure 4) suggest elective cognitive selection to harness desired performance. Considering the multi-intelligence theory to enhance decision-making through all CI processes of collection, analysis and dissemination, the decision-maker needs different skills at each stage; skills can start with strategic thinking, articulating ideas, and communication (Power, 2014). For example, decision-makers with highly developed interpersonal and linguistic intelligence can further be distinguished during the dissemination process rather than analysis process.

A recent study about resetting decision-making in organisations has confirmed that decision-making is a dynamic process that evolves with the company's performance, and it must clearly align with its strategic objectives (Christine, 2021). Decision-makers, as a mere truth, seek pertinent information, with a reduced probability and uncertainty (Adrian, 2017) and less similarities (Norris et al., 2020) to achieve certain objectives; This information is used to constitute two types of decision: operational and strategic (Gilad and Gilad, 1988). The difference is that strategic decisions place higher influence on the information's quality rather than timing and speed. In addition, an extant study examined the main topics of information that reach decision-makers. Koseoglua et al. (2019) reported that middle and lower levels of related CI specialists have knowledge of CI restricted to the customer's experience and competitors. This means that since the CI community provides information to the decision-maker in the first instance, knowledge limitations constitute a fundamental challenge for the decision process.

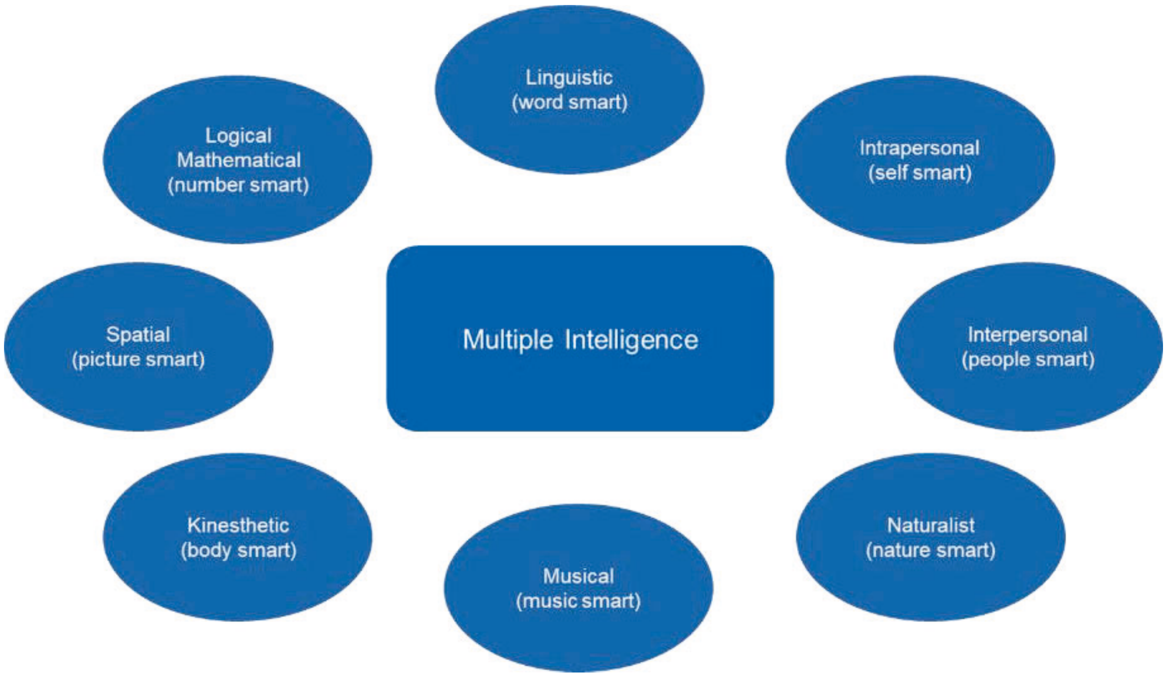

Figure 4 Theory of Multiple Intelligences, adapted from Howard Gardner (1990)

In a proposition that advocates a systematic approach to knowledge formation reaching decision-makers, academic research suggests that solid knowledge management can certainly improve organisational performance and will form a consistent strategy that is able to evaluate and improve the decision-making model (Norris et al., 2020; Herden, 2020; Cohen and Olsen, 2015; Sundiman, 2018).

2.5.1 Knowledge

"Managing knowledge is 10% about technology and 90% about human resources" (Global intelligence alliance, 2007a).

Knowledge was considered a metaphorical structure (Lakoff, 1980) that creates a mapping function from a source field to another target field; to create better understanding (Ortega et al., 2002). The mapping process has been assimilated as the association between physical and conceptual fields (Maasen and Weingart, 2005; Andriessen, 2008). Nonaka (2009) claims that knowledge has two types: tacit and explicit. Both are valuable to form efficient decision-making (McKenzie et al., 2011). Subsequently, this leads to considering knowledge as any concept perceived important (Carlile and Rebentisch, 2003), which can be utilised according to the context.

Since knowledge rests on individual's readiness (Olafsen et al., 2021), it is worth mentioning the trilogy of mind theory (Hilgard, 1980), which stands for self-consciousness or reflection toward attaining knowledge through three pillars: affection, cognition and volition. Knowledge is formed through the experience of feeling together with the thinking process, both comprise affection and cognition. Volition is the substantial component to complete knowledge acquisition through emphasizing an individual's mental process to initiate the action (Hilgard, 1980). In some situations, Keller's (2010) ARCS model of motivational design appears preceding the process of knowledge constitution through employing the oriented person in the most centred environment supported by interactional instructions. Bateman and Hess (2015) described it as omnibus models if it incorporates the teaching system. The mathematical theory of communication (Shannon, 1948) also draws a schematic diagram of a communication system between information source and receiver. Language is considered as a discrete noiseless channel, which can also perform as a path broadcasting strength (Amico et al., 2019.) In fact, language is concluded to be a legitimate step between stimulus situations in the knowledge formation process (Levenson and Hagnell, 1967).

In line with the above discussion, it is assumed that knowledge generation is most appreciated, primarily when utilised in the applied research context. While early research focused on generated knowledge, through the knowledge-based view, as a critical resource for the organisational outcome (Côrte-Real, 2017). Ghasemaghaei et al. (2017) emphasised knowledge dissemination and sharing to enhance decision-making. Despite an individual's filtering process, Connelly et al. (2014) explained knowledge sharing as a tool capable of saving time and cost. If satisfactorily employed, leaving no need to "reinvent the wheel" looking again for the information.

In regard to the knowledge-based view (KBV), which is considered as a sequence of the resource-based view (Andriessen, 2008; Connelly, 2014; Herden, 2020), it adequately recognises knowledge as the main strategic productive resource because it is unique and inimitable (Nonaka and von Krogh, 2009). In fact, the KBV first addresses knowledge exchange through a managed and efficient hierarchy, next it presents knowledge as the main strategic asset for managers (Grant, 1996, Nickerson and Zenger, 2004) to sustain the organisation financially, and to sustain its competitive advantage.

Since this study intends to apply BDA within the competitive intelligence process, utilising the attained knowledge towards efficient decision-making, the knowledge-based view gives a sufficient theoretical grounding to explore the generation of competitive intelligence from analytics.

2.5.2 Decision-Making Model

The literature has led to a greater appreciation for exploring and investigating human behaviour in the decision-making process, in particular through a bounded rationality aspect (Kalantari, 2010; Simon, 1977). In fact, Katsikopoulos and Lan (2011) have concluded that most researchers follow either the prescriptive or descriptive goals of Simon's decision-making model (Simon, 1972). Simon's model comprises of four processes of intelligence, design, choice and implementation phases, emphasising procedural rationality rather than substantive rationality (Simon and Hayes, 1976).

Remarkably, the DeCoAgent model (Rao and Georgeff, 1995) is similar to Simon's processes, except for the last phase of execution rather than emphasising monitoring. It seems that Simon believed that the last phase could develop disciplines assistance, especially for irrational decisions that are based on stress and emotions (Simon, 1955).

On the other hand, Thagard's (2002) deliberative coherence model is constructed based on more representational factors like images and motions, which can fit (cohere) or resist fitting (in-cohere) together. Thagard's model provides situational awareness for decision-makers to adapt and lead through a connectionist network. However, Yilmaz et al., (2017) have found that Thagard's model is better when compiling it with another reflective model, like the ethical decision-making model (Howlett and Ramesh, 2003), because it will help the process to function strategically while advocating all principles required.

Drummond and Niv (2020) claim that two decision-making systems reside in the brain: model-based and model-free. Each system has an equally valuable approach to guide actions according to the context. The two systems work simultaneously; however, the brain arbitrates between the two systems according to uncertainty. It seems that decision-makers hold personal beliefs that link between action and outcome (Arnold et al., 2004). This allows response prediction probabilities of the "learning model" (Rescorla and Wagner, 1972) to understand environmental signals. This is why Dilanian and Howard (2020) stressed the necessity of leaders' capability to work and decide without supervision, but, it is also important for them to utilise the feedback loop proposed by Yang et al. (2017), which aims to solve any existing divergence accrued during the decision-making process.

A recent study proposed a new decision-making model (Wang, 2020) based on constructing similarities between current and historical scenarios. An action plan will be generated based on utility value for the target scenario. Also, Holmlund et al. (2020) suggested a step-by-step guide model for decision-makers who adapt big data technology, proposing to apply sequential actions for each instance of decision-making. Steps are Strategies, assess, examine, decide, implement, and learn.

Based on the literature review, a conceptual model (Figure 5) for the decision-making structure was developed to help the researcher proceed for the main research problem.

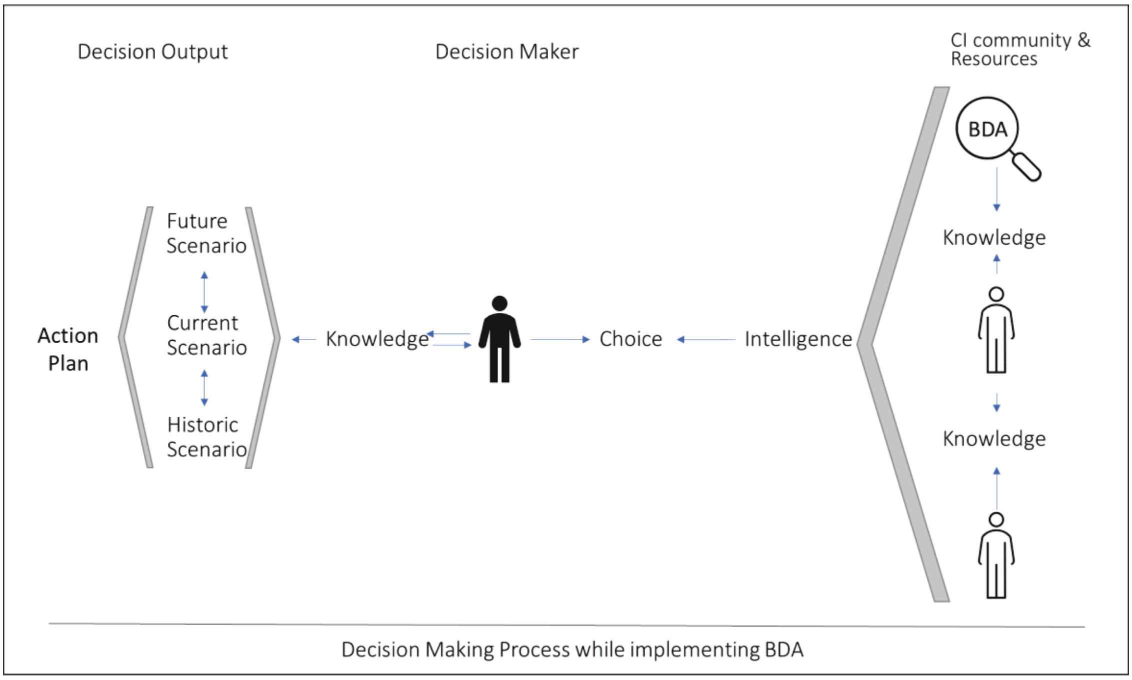

Figure 5 Decision-making conceptual model for this study

2.6 Marketing Mix

The complexity of the competitive environment, primarily through BDA technology, calls decision-makers to recognise multiple aspects to select marketing tactics. Corporate marketing practices have utilised the 4 P's (McCarthy, 1968) as a base for marketing decisions, monitoring Product, Place, Promotion and Price. Additional P's of Physical evidence, People and Process were added to the marketing mix model, demonstrating 7 P's (Booms and Bitner, 1981) of key marketing elements.

Numerous research has called for integrating the 4 P's and 7 P's into a strategic construct to develop new foundational theories for the marketing discipline (Perera and Hewege, 2016; Cooper and Naatus, 2014; Sloan, 2015; Whitehurst, 2016). Lauterbom (1990) proposed the 4 C's in his article "New Marketing Litany: Four P's Passe: C-Word Take Over". He proposed a shift to a consumer-centric model that looks for Consumer wants and needs, Cost to satisfy, Convenience to buy and Communication.

Marketing decisions consider the current strategic context to plan for the organisation's marketing activities. Current technological complexities and the social media context have posed a question of the adequacy of the marketing mix model. Calls for revising the 4 P's and 4 C's models to meet with today's marketing functions (Intyas and Primyastanto, 2020; Ville et al., 2020; Ettenson et al., 2013)

The SAVE framework, which stands for Solution, Access, Value, and Education (Ettenson et al., 2013), changes the way products and advertisements are seen and characterised. The framework claims to engage in the marketing atmosphere, helping to produce marketing content that helps to sell the product. Another approach claims to include ethics, integrity and social responsibilities towards marketing tactics; the Guiding Principal Model - GPM - by Philip et al. (2018) proposed a strategic framework of Mission, Intelligence and Responsibility as an innovative and holistic pedagogical tool towards marketing decisions.

2.7 CI Process

Competitive intelligence is a process of linked phases (Iwu et al., 2020; Nasri, 2011). The cycle of each phase greatly influences decision-making (Krishnan, 2021; Wright and Calof, 2006). In order to reach for the desired intelligence, it is important to have a structured process of competitive intelligence activities (Bose, 2008). Several articles have described the process cycle; however, each has its own emphasis on the cycle according to the study's objectives, and because the CI process structure has to fit each organisation's goals, it is expected to have no blueprint for a CI process (Adeline and Marie, 2004) that works for all.

It is essential to mention that the literature review has revealed several models of CI process that touch upon system structure and decision-making attributes (Allison, 2021; Van Den Berg et al., 2020; Adrian, 2017; Yin, 2018; Madureira et al., 2021). Digital marketing instruments have been abundantly discussed in the literature as an opportunity to achieve competitive advantage (Mikalef et al., 2019; Salleh and

Janczewski, 2016; Sun et al., 2020; Kumar et al., 2020; Ranjan et al., 2022). As for BDA implementation throughout CI process, it has been discussed lately in terms of how organisations deal with BDA, highlighting only on challenges of adapting the technological factors into the business and operations (Ekka and Jayapandian, 2020).

According to well-established theories and previous empirical studies about competitive intelligence (Kumar et al., 2020; Herring, 1992; Calof and Dishman, 2002; Badr et al., 2006; Gainor and Bouthillier, 2014), three main aspects have been commonly identified as the process of CI: organised list of required information, system for collecting sourced, stored, analysed, shared data, and a technique to inform decision-makers of the intelligence results. All studies have identified the strength of decision-making to operate CI, highlighting possibilities to improve decision outcomes as the ultimate purpose of intelligence. On the other hand, the studies omit influential factors that help to disseminate results.

Other phases of competitive intelligence were also discussed in the literature; Calof and Wright (2008) recommend four cycles for CI: planninging, collection, analy,sis and communication. The model covered all related work of collecting and analysing information; however, it omits aspects of information storing and feedback. Sawka and Hohhof (2008) introduced the process as an interrelated phases of planning, collection, analysis, production, and dissemination. The model has not emphasised related influential factors like decision-making outcomes. Reinmoeller and Ansari (2016) claimed the CI process starts with monitoring, gathering, analysis and dissemination. The model did not incorporate information storing and feedback.

A recent approach claimed that skills and time are the two essential elements to construct competitive intelligence (Madureira et al., 2021). The time orientation is concerned with future aspects through strategic insights that support the tactical ones. The other element of intelligence practice is the need for both individual and organisational capabilities. This element helps in learning and implementation, as well as influencing decision-makers. Kahaner (1996) proposed a cycle of planning, direction, data collection, analysis, and dissemination. The phases were similarly adapted by Cruywagen (2002), who introduced the CI process as: planning, direction, collection, evaluation, analysis, and dissemination. This process has also been identified in other studies (Bose, 2008; SCIP, 2007; Yin, 2018) with the addition of the feedback phase after dissemination. It has also informed the CI's process model by Saayman et al. (2008), with the addition of the phase of establishing the needs, instead of CI planning phase. The models allow for the incorporation of feedback; however, it requires more explanation of data capturing.

Rouach and Santi (2001) proposed a model that examines the organisation's scientific and technical assets while relating them to competitors' assets. The process starts with incubation, conception, implementation, structuration, and finally, evaluation. The model calls for the organisation to achieve successful technological options, bring value to information, and transmit it. Fleisher (2008) proposed similar attributes of the CI process: scanning, finding, collecting, evaluating, validating, analysing, and sharing. Also, Gates (1999) pointed out the electronic-based factor within the CI process. The study claimed that technology should gather and manage numbers, sounds, photos, and text, then digitalise and disseminate them. Gates stressed the last phase, claiming that organisations might still fail to achieve competitive intelligence if employees did not select the right information at the right time to be used.

Köseoglu et al. (2019) provided a CI model (Appendix A) starting from of the strategic level perspective that produces the formation of CI. The model is primarily operated by the CI pool, which categorises the organisation's activity as either specific which is relates to long-term goal of competitors and customer strategies, or it is general of day-to-day tactical business activities.

Informed by the critical evaluation of related models and considering the aims and objectives of this study, Pellissier and Nenzhelele's (2013) competitive intelligence model appears more relevant to the context. Despite the dissimilarity of how CI is initiated, it was inspired by Saayman's et al. (2008) model (Appendix B). The model (Figure 6) comprises a cycle of interrelated phases, investigating the output of one phase as an input for the next. Throughout the entire CI cycle, the organisation has to provide trenchant formal and informal policies and procedures, helping employees to contribute effectively towards the CI process, and to create appropriate internal organisational awareness, facilitating feedback for decision-makers.

Figure 6 CI process model, adopted from Pellissier and Nenzhelele (2013)

Applying the model to the context of this study, there was a need first to eliminate ambiguity and provide clear outlines on how a CI committee plans and gives competitive strategy directions. The second phase allowed for an in-depth understanding of current information collection tools, highlighting the specific BDA source used with justifications for why it has been selected. Next, information processing and analysis were discussed, exploring when and how technology effectively replaced human resources through the BDA tool. Finally, the information dissemination phase highlighted how the CI decision-makers disseminate the acquired actionable insights. This phase demonstrates critical propositions for the organisation, whereby this study was able to recommend best practices of the CI process through effective BDA.

Van Den Berg et al. (2020) provided a rational explanation study, coding 61 articles discussing the CI process through Pellissier and Nenzhelele's model. The study unveiled more detailed codes (Table 2) for each process phase, including similarities of centrally faced influential factors. Understanding the influential central factors will support this research process in drawing between CI phases. For example, managers tend to adopt a certain attitude concerning implementing an ambiguous change into their organisations (Brânzaş and Radu, 2015). If this is the case, this means utilising resources of the competitive environment are limited because of the ambiguity of the strategy; and accordingly, the process between phases may be shorter due to fewer intelligence inputs communicated to decision-makers.

Adrian (2017) claims that decision-makers, as the main influential factor of the CI process, should assimilate all aspects of the CI process, such as: selecting specialists' skills, technology to be used and how, and information communication. In fact, decision-makers of competitive strategies should have the ability to address issues of poor identification of key intelligence needs (Maungwa and Fourie, 2018) and expect and predict results in each CI phase (Adrian, 2017). Most importantly, controlling the last cycle of evaluating the CI function and comparing it to business objectives is the key success of CI, because it is responsible for delivering the intelligence mission (Maungwa and Fourie, 2018).

Table 2 Common codes of Pellissier and Nenzhelele's (2013) CI process model, adopted from van den Berg et al. (2020)

Interrelated Phased			Central Influential Factors	
Key needs	knowledge of CI specialist	Problem solving	Competitor's knowledge	Process models
CI specialist's skills	Deal with technology	Sharing & feedback	Environment knowledge	Skills & training
information characteristic	Specialist skills	Information collector	Strategy	Formalised structure
Reliability	Key topics	Relationship	Purpose	Resources
Problems encountered	Systems & data mining	Communication	Benefits & evaluation	CI culture

2.8 Big Data

Big data is an emerging topic among scholars and practitioners. Rich (2012) identified 'Big Data' as a dataset derived from different channels. Manyika et al. (2011) described it as a non-typical dataset of database software that captures, stores, manages and analyses information. It aims to generate actionable insights and help the organisation to sustain its business values (Fosso Wamba, et al., 2015).

The advent of big data is becoming a global term for the technological complexity that aims to analyse mostly unstructured big volume data, where traditional tools3 cannot handle it. The notion of 'V's' has been commonly used in defining big data in the literature (Hosseinian-Far et al., 2018). To summarise what the "V's" mean:

- Volume: data requires huge storage capacity or contains a substantial number of records (Russom, 2011; Sivarajah et al, 2017). The Volume characteristic can be quantified through Terabytes, Records, Transactions, Tables (Armour, et al., 2011). Apache Hadoop and Map Collapse is the most established software platform for analysing large amounts of data (Gupta et al., 2018).
- Variety: Data generated from a greater variety of sources and formats (structured, unstructured, semi-structured) and containing multidimensional data fields (Russom, 2011; McAfee and Brynjolfsson, 2012). Apache Drill is an example of a software product that adapts flexibly to query language, data format, and data source type (Gupta et al., 2018).
- Velocity: Frequency of data generation and/or frequency of data delivery (Hallikainen et al., 2020), for example real time and streams. It has been reported that velocity is the most significant big data characteristic that would affect a firm's performance (Ghasemaghaei and Calic, 2020). Apache Spark is an example of a framework built for sophisticated analysis and processing at high speed (Gupta et al., 2018).

3 Traditional data is generated at the enterprise level and deals with structured data generated per hour or per day or more. It is managed in a centralized form of a volume ranging from Gigabytes to Terabytes (Satyabrata, 2020)

- Veracity: Facing the uncertainty of data, particularly from social networks and the Internet of Things (Al-Jepoori and Al-Khanjari, 2018), it is required to achieve analytics of reliable predictions (Beulke, 2011), aiming to control the most challenging quality and accuracy (Chandralekha and Shenbagavadivu, 2017).
- Value: Clear business road map enables organisations who utilise big data to extract insights that save money for long and short periods (Gartner 2012; Saporito, 2013). In fact, the potential for big data is expected to impact all sectors, from healthcare to media, from energy to retail (Manyika et al. 2011).

It is clear that big data was created by the widespread diffusion and adoption of technology and the 'Internet of Things' related concepts, primarily to improve organisations' performance (Ghasemaghaei et al., 2017). The importance of big data to business is derived from the ability to analyse this technology, provide valuable insights that can improve decision-making and reinforce business outcomes through quantifiable and translucent reports (Boyd and Crawford, 2012).

Despite the fact that "big" can instinctively be referred to size, the term is referred to impact and mindshare of the phenomenon (Faraway and Augustin, 2018). Organisations, to attain a big impact, need statisticians who can analyse substantial and machine-analysed data to predict insights of market and consumer behaviour (Theriot, 2014). In this sense, it is important to mention that small data does also provide impact and organisationally valuable insights (Tirpak, 2017).

Small data is characterised by tightly controlled data production that is limited in volume, velocity, variety and uncertainty (Wang et al., 2020), and it is usually generated to answer specific questions. For example, qualitative data like interview transcripts for a limited respondent number. Small data can thus highlight certain cases (Smilansky, 2016) and provide nuanced and contextual stories.

It is narrow versus open mining (Lauriault, 2012) when comparing between small and big data. Sampling frame, technology and platform used, data ontology, context and regulatory environment (Kitchin and Lauriault, 2015) are all what shapes the data captured. This study focus is exclusively on big data and the associated analytics of predominately information and communication technologies, characterised with the 5 V's.

2.9 Big Data Analytics (BDA)

Information technology (IT) has been covered intensively in the literature, and the capabilities impact on organisational performance is appreciated. Although the link between IT capabilities and organisational performance remains indecisive (Stoel and Muhanna, 2009), organisations have started to harness cutting edge technologies, in particular, to achieve competitive advantage. In fact, IT capabilities are a key determinant of competitive advantage (Ekka and Jayapandian, 2020; Chen et al, 2012), and it seems that decision-makers who adapt innovative technologies as an organisational competency are more likely to endure better competitive performance (Nwankpa and Datta, 2017, p. 470).

Based on the Resource-Based View-RBV-, an organisation's competency involves tangible, intangible and human resources that serve as potential sources of competitive advantage (Bharadwaj, 2000). Physical assets like IT infrastructure are a source of competitive advantage only if they outperform other competitors (Barney 1991; Mata et al. 1995). Rivals cannot easily resemble other organisational competencies of IT infrastructure, because utilising human skills is also important to translate IT resources in achieving business goals and objectives (Allison, 2021). For example, combing available IT infrastructure with strong human skills enables intangible competencies like knowledge and customer management.

In the context of creating competitive intelligence while utilising IT capabilities in which big data is part of IT investments and infrastructure, decision-makers will ask "how investing in big data can turn into core competency and enhance competitive intelligence?" Indeed, the ability to utilise big data investments to achieve valuable insights of competitive advantage and success is a critical factor (Côrte-Real, et al., 2017) for practitioners and researchers. Erevelles et al. (2016) claims that organisations who are unable to develop big data applications will struggle to sustain their competitive advantage.

Since big data is useful only when we use the data in analyses (Power, 2014, p.225), and while competency refers to any process that leads to valuable outputs (Nwankpa and Datta, 2017), BDA or "discovery analytics" (Russom, 2011) challenge decision-makers to find evidenced-based patterns and make sense of it to facilitate performance as a valuable IT competency (Ghasemaghaei and Calic, 2020). Labrinidis and Jagadish (2012) simplified the definition as the method used to examine and attain intellectual insights from a large dataset. In an interview discussing the competitive advantage with Tom Davenport, an academic and author specialising in analytics, he said, “it is the systematic use of data and analysis to drive decision-making and action” (Davenport et al., 2017). Worth mentioning, an earlier study by Davenport and Harris (2007) have claimed that knowledge is useful, beneficial, and able to create a competitive edge. A report by data and analyst hub IDC-iview described big data technology and analytics as the new generation of technologies and architectures, designed to economically extract value from very large volumes of a wide variety of data, by enabling high-velocity capture, discovery, and/or analysis. (Gantz and Reinsel, 2011).

While some studies have investigated IT capabilities and competencies based on the theoretical foundation of Resource-Based View -RBV (Bacq and Eddleston, 2018, Bharadwaj, 2000, Wu et al., 2016, Lioukas et al., 2016, Melville et al., 2004, Ruivo et al., 2015, Zhu and Kraemer, 2005), and despite the fact that BDA is considered to be part of IT capabilities, it appears that the Knowledge-Based View – KBV in combination with Dynamic Capabilities theory - DC (discussed previously) is more relevant to the objectives and results of BDA of this study context. The IT capabilities embraced by analytics technology, forms, reports, and data management explore the intelligence potential to obtain competitiveness in a dynamic market context, using the acquired knowledge to leverage productive outcomes. The possession of knowledge resources, formed by BDA, enables an organisation to reconfigure its resources and build dynamic capabilities (Côrte-Real, et al., 2017).

Despite the fact that analytics capabilities have no inveterate value (Seddon et al., 2017), the insights produced will integrate into the competitive intelligence process, producing knowledge of patterns that is required for insight-driven decision-making (Kiron et al. 2012; Seddon et al. 2017). In fact, decision-makers need BDA for its ability to produce regenerative actions, provide unexplored opportunities, enhance product offerings, satisfy customer needs faster and elevate innovation performance (Calvard, 2016; Du and Kamakura, 2012; Ghasemaghaei and Calic, 2020; Johnson et al., 2017; Satell, 2014).

Given that BDA is a major determinant of organisational performance (Liu et al., 2020; Ekka and Jayapandian, 2020; Davenport, 2013), the automation of decision-making based on innovative technology is required to establish a solution that can eliminate ambiguity (Daft and Lengel, 1981) and reduce user effort like avoiding repetitive results (Herden, 2020).

In a similar vein, recent studies have attempted to investigate the relationships between BDA and decision-making performance. It seems that to achieve an adequate level of both analytics and decision-making success, human analytical skills remain necessary for decision-making (Roßmann et al., 2018). Ghasemaghaei et al. (2017) claims that there is a significant relationship between employees' analytical skills and BDA towards achieving the desired performance. Human inputs, management and interpretations are critical and cannot be replaced by technology (Johnson et al., 2017). Moreover, the human aspect is important to identify objectives, and determine types of desired analytics. decision-makers should not invest exclusively in collecting large amounts of data (Ghasemaghaei and Calic, 2020, p.158); because there are different analytics types that vary in value, but all perform usefully to the organisation.

Because big data has been described as a business opportunity (Russom, 2011), five types of BDA methods (Figure 7) have been identified in the literature (Sivarajah et al, 2017) to produce valuable intelligence insights:

- Descriptive analytics: "What has happened?"

Deriving insights from the past (Yasmin et al., 2020) to define current state of business. Example: business and marketing reports, KPI's, scorecards reports. Proposed techniques: data modelling, trend reporting, regression analysis and correlations. Data scientist, Michael Wu, said that more than 80% of business analytics are descriptive, and based heavily on social analytics (Jeff, 2013)

- Inquisitive analytics: "Why it happened?"

Inquiring data to validate/reject business hypotheses (Ghasemaghaei et al., 2017). Example: probabilities analysis, case study reports that aim to investigate certain factors and causes. Proposed techniques: sensitivity analysis, and conjoint analysis, statistical analysis, and factor analysis. It is worth mentioning that techniques of descriptive and inquisitive analytics go hand-in-hand in most organisational structured environments (Cheng, et al., 2018).

- Predictive analytics: “What could happen?

Offering in-depth insight to assist future strategic questions and concerns using past and/or current data and show possibilities or relationships stemming from each factor (Esmaeilbeigi et al., 2020). For example, sales forecast reports, competition, consumer analysis, customer relationship management, talent management, risk and growth management (Simos, 2018). Proposed techniques: data statistical modeling, predictive modeling, and text mining, Event Stream Processor (ESP) and sentiment analysis.

Hallikainen et al., (2020) claims that predictive analysis helps companies avoid costly errors specially related to stock inventory. For example, Walmart has reported utilising big data predictive analytics, and results showed a reduction of 20 minutes in the time from spotting a problem to proposing solutions (Marr, 2016). Also, while predictive analysis can play an essential role in managing customers and eliminating complaints (Holland et at., 2020), it is also possible to manipulate results to achieve customers’ loyalty (O'Flaherty and Heavin, 2015).

- Prescriptive analytics: “What to do?”

Building on the previous predictive analysis, prescriptive analytics aims to enhance the business level by advising on certain anticipated impacts for certain cases or scenarios, aiming to provide different decision choices for decision-makers (Beulke, 2011; Ghasemaghaei, 2020; Johnson et al., 2017). It begins by identifying the problem and giving a specific question for a certain event to happen. The analysis examines data with other data criteria (Imanuel, 2015) seeking to eliminate options of outcomes (Hallikainen et al., 2020) and predict action consequences (Chandralekha and Shenbagavadivu, 2017) through measured key performance indicators (Islam et al., 2015). Eventually, it recommends actions for the main problem.

As per Gartner’s report for the period from 2017 to 2022, 20% CAGR growth is expected for prescriptive analytics software utilisation (Alys et al., 2019), offering the product roadmap an additional value for decision-making capabilities. However, decision-makers need to acknowledge the difference in practice needs between organisations; the prescriptive analytics model is usually tailored to case (Hallikainen et al., 2020), and what fits one case or organisation may not fit another. Moreover, ethics should be closely monitored (Bratu, 2018; Fuchs, 2017; Metcalf, 2016; Nersessian, 2018) especially when analysing human behaviour based on computer interpretation, and a clear governance strategy (Cheng et al., 2018) is required to avoid invalid results.

- Pre-emptive analytics “What is required to do more?”:

It is a preventive intelligence to take action on events that may undesirably affect organisational performance (Sivarajah et al., 2017). This type can detect root caused by imminent network incidents (Marjani et al., 2017) and provide actionable insights of crucial understanding, of the client of tomorrow, ahead of time. In fact, business survival may depend on the capability of rapid response (Smith, 2012). For example, in a study by Coetzee (2018), it is claimed that banks can adapt pre-emptive analytics to capture systematic risk of bank failure before it happens, to ensure the permanence of its regulatory framework.

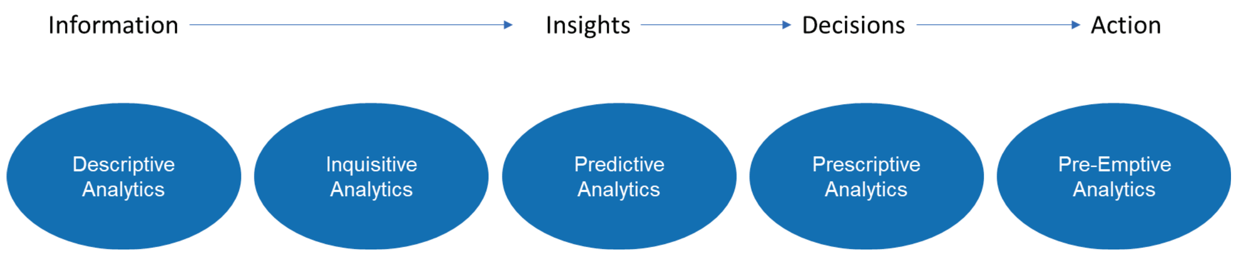

Figure 7 Types of BDA, adopted from Sivarajah et al. (2017)

While big data uses real-time sources of information, it is possible to anticipate the impact of organisational goals (Wamba et al., 2015) and provide predictive-estimative analysis. Davenpot and Patil (2012) claim that big data outcomes have better accuracy while predicting the future. Though, a mismatch is reported between theoretical performance of BDA and the actual real-life performance (Otero and Peter, 2015). According to Gartner Research, “management resistance and internal politics” are a serious obstacle to achieving the desired machine learning algorithms. Indeed, it leads to a waste of machine time and slowdown per task (Rosa and Binder, 2017) thus, a misconfiguration task shall occur and will induce unsuccessful executions of jobs (Sun et al., 2020). In this respect, Henrion (2019) calls to formulate sufficient organisational alignment, enriched with middle management adoption to avoid business resistance of growth promising resources.

Firms who believe in BDA are keen to acquire the best tools to predict and determine behaviour on a large scale, so they can make effective decisions and gain higher market share (Serra et al, 2018). A recent statistic report shows that "the customer analytics market size is projected to grow from USD 10.5 billion in 2020 to USD 24.2 billion by 2025" (Anon, 2020). As firms seek to reduce operating costs, produce better products and services, and achieve profits and growth, they need data visualisation practice to translate big volumed data into a visual context (Louridas and Ebert, 2013) like graphs and tables, so they can extract insights that are easy for the human brain to understand.

Blue Apron, the meal kit delivery service, uses predictive analytics to forecast demand (Gavin, 2019). The company's engineering team have successfully built a forecasting model that can understand customer behaviour and recognise their taste preference. The predictive models have achieved a high level of accuracy and resulted in the business providing a satisfying recipe offering every week.

Algorithm visualisation and statistics are useful if strategically approached (Nair, 2016), but the biggest challenge revolves around having no particular standard to follow for visualisation and statistic tools. Organisations can either proceed with an open-source tool or a proprietary tool. Apparently, the latter is more expensive but has a simpler drag and drop nature of coding (Serra et al, 2018). The statistical capabilities and programming languages vary (Louridas and Ebert, 2013), each have statistical sophistications for their users that serve certain business objectives.

The cost-effective open-source software simply means that the source code is available and editable (Ames et al., 2019) by the end-user, i.e., KNIME Analytics Platform, RapidMiner, RStudio, Apache Spark, and Pentaho Platform. On the contrary, proprietary visualisation tools are mostly business intelligence (BI) tools, i.e., Tableau, Zoho Analytics, Splunk, SAS, Cassandra, SiSense, COGNOS, PowerBI, QlikView, and Spark.

Big data software, as an infrastructure and analytic tool, is meant to "support the time-constrained processing of continuous information flows to provide actionable intelligence" (Otero and Peter 2015) that is more than simply finding or summarising data (Nair, 2016). Apparently, big data software comprises of three substantial areas: insights of solutions needed rapidly for immediate and time-constrained use, big data of continuous information flows demonstrating the V’s characteristics, and finally providing results that are useful for business decision-making.

The information flow of big data software varies in the literature in terms of data sources and communication perspective. A recent study by Khan (2020) demonstrated the flow through four layers. The first layer is composed of sources of different formats, point of collection, time stamps, and periodicity. In this level, pre-filtering techniques are applied to produce data in clear format and meaning. The second layer, after having data installed in a different location, involves device-to-device processing to convert data into a manageable format. The third layer’s purpose is to generate data processing and data storing by integrating offline data processing like Hadoop, with a real-time data processing system like Spark, Storm, etc., and data storing like HDFS, HIVE. The fourth layer is called the service. It functions as an intelligent system providing the desired interfaces to the proposed system, which is controlled by human and other objects, for injecting and collecting information.

Facebook is a major influential software and platform tool for BDA extracting real-time reports (Henschen, 2013). Hive is a data warehousing infrastructure that is used by Facebook to generate reports, also Scuba is used by Facebook as a memory platform to store everything, making drilling down information fast and easy.

A simpler information flow has been proposed by Otero and Peter (2015) and has been distinguished in other articles (Lan et al., 2019; Wang et al, 2018), which is the single-hop processing and multi-hop processing of continuous information flow. The single component verses multiple component is the main difference while providing the results of the analysis. Using multi-source like twitter, YouTube, and Instagram, all at the same time, would make the system more complicated when detecting inconsistencies in the output.

To concise the information flow of big data software, three terms must be identified. Data acquisition, data analysis and value discovery, and use case consolidation (Kourla et al, 2020). Data scientists will be required to collect big data for data repository. Data analysis is next performed using machine learning, text and predictive analytics, data mining, deep learning, natural language processing and information technology. Finally, consolidating insights are derived using the results values, by forming models for presentation and discussion.

2.10 Organisational Intention to Adopt BDA

It has been long known in business that an organisation's ultimate goal is to provide the market with a product or service that is difficult for competitors to imitate. Big data is a valuable resource to drive competitive performance gains. However, organisations are triggered by various factors that can stimulate the intention to adopt this new technology and leverage results of analytics.

It seems that organisational culture embodied in top management support, and organisational learning and employee competencies (Salleh and Janczewski, 2016) are initial indicators in showing whether an organisation will or will not adopt BDA in the business reporting system. Furthermore, the IT infrastructure, especially if it is highly facilitated, can be considered a motivating condition in influencing big data adoption (Queiroz et al., 2019). Further factors too were investigated and reported as organisational influencers in adopting big data, particularly in the B2B industry, which are competitive pressure, relative advantage, and the regulatory environment (Sun et al., 2020).

Nevertheless, there are factors affecting the organisation's intention not to adopt big data and persist with traditional business methods, like reports initiated by individuals (Sanjay and Nishant, 2015; Aljumah et al., 2021). Mahesh et al. (2018) claims there to be a significant negative association between complexity and environmental uncertainty towards big data technology adoption. As a matter of fact, investments in BDA do not necessarily lead to the anticipated results value (Surbakti et al., 2020), especially if the organisation seeks to capture and master all types of analytics at once, or extract all types of insights (Holmlund et al., 2020).

Each organisation orchestrates differently to leverage the desired business performance, and because big data is expensive and requires challenging tasks, an organisation shall operate according to its own ethical attitude, privacy and security procedures (Salleh and Janczewski, 2016). Competitive performance is claimed to be achievable if the organisation has a renewed operational capability and is able to acquire a mixture of technological, human, financial, and intangible resources (Mikalef et al., 2019).

2.11 The Proposed Model of Artefact

As per DSRP, the problem identified was the lack of a generic process model for the competitive intelligence process combined with BDA adoption, and the objective was to create a novel model of process elements and descriptions that could be adopted by experts working in this area of the discipline.

The scope of the model is restricted to two conditional subjects - CI and BDA - that must both be functioning in the organisation. It applies to the real estate industry in the UAE, both governmental and private medium to large-sized firms, because data is accessible and obtained for both. The scope excludes organisations who run marketing campaigns on an extremely low scale in either digital or traditional marketing channels, and small organisations are excluded.

1.11.1 Fundamentals of the Model

Montasari (2016) stressed the importance of having standardized terminology while composing models. Therefore, the study is cautious to choose rigorously and widely accepted (Kohn et al., 2013) terminology within the marketing context. Based on the literature review, highlighting on CI activities components to enhance organisational performance (Chouder and Chalal, 2014; Yin, 2018), some key elements are fundamentals while illustrating the process:

1. The process must achieve actionable intelligence
2. Credible and trustworthy
3. Clear definitions of project community
4. Adapt the knowledge and learning factors

2.11.2 Identifying Necessary Elements for CCIP-BDABM

As part of the thematic literature review, a manual exercise of identifying the key themes and keywords undertaken in prior studies for CI and BDA are summarised, to help construct the conceptualised proposed model.

This comprehensive review and thematic analysis (Appendix C) was conducted to reach and form elements of the proposed Comprehensive Competitive Intelligence Process- BDA Based Model (CCIP-BDABM).

The primary task of the integrated elements is to smoothly produce knowledge and valuable insights that are more related to the organisation's concern of acquiring competitive advantage and enhancing business performance. By synthesising the key themes and keywords as well as considering the reviewed models collectively, the necessary elements for the CCIP-BDABM are now summarised as follows:

1. Inception of intelligence need has two sources; long-term organisational perspective, where the firm plans for business strategically, and short-term perspective represented by tactical and operational business direction.
2. Big data solution will support knowledge flow without any setback.
3. Big data software is an additional competitive intelligence tool, which the firm can use when it is appropriate.
4. CI community can steer and monitor both traditional and big data tools in order to extract the desired intelligence.
5. Extent of CI community required while utilising BDA is obscure.
6. Decision-maker is expected to take part when initiating intelligence need, and when receiving insights, and at the end when monitoring the implementation of the action plan.
7. Big data solution can be utilised throughout CI process, or through parts of it according to objectives and insights required.
8. Intelligence dissemination harbours innovative value for exploration.
9. Monitoring is an essential final stage, which can be an input for another new CI cycle.

Figure 8 presents the (conceptual) proposed model, which outlines a series of concepts and their relationships. By completing the steps of DSR, this conceptual model will be further improved and updated throughout a series of iterative interviews with experts, forming the final model.

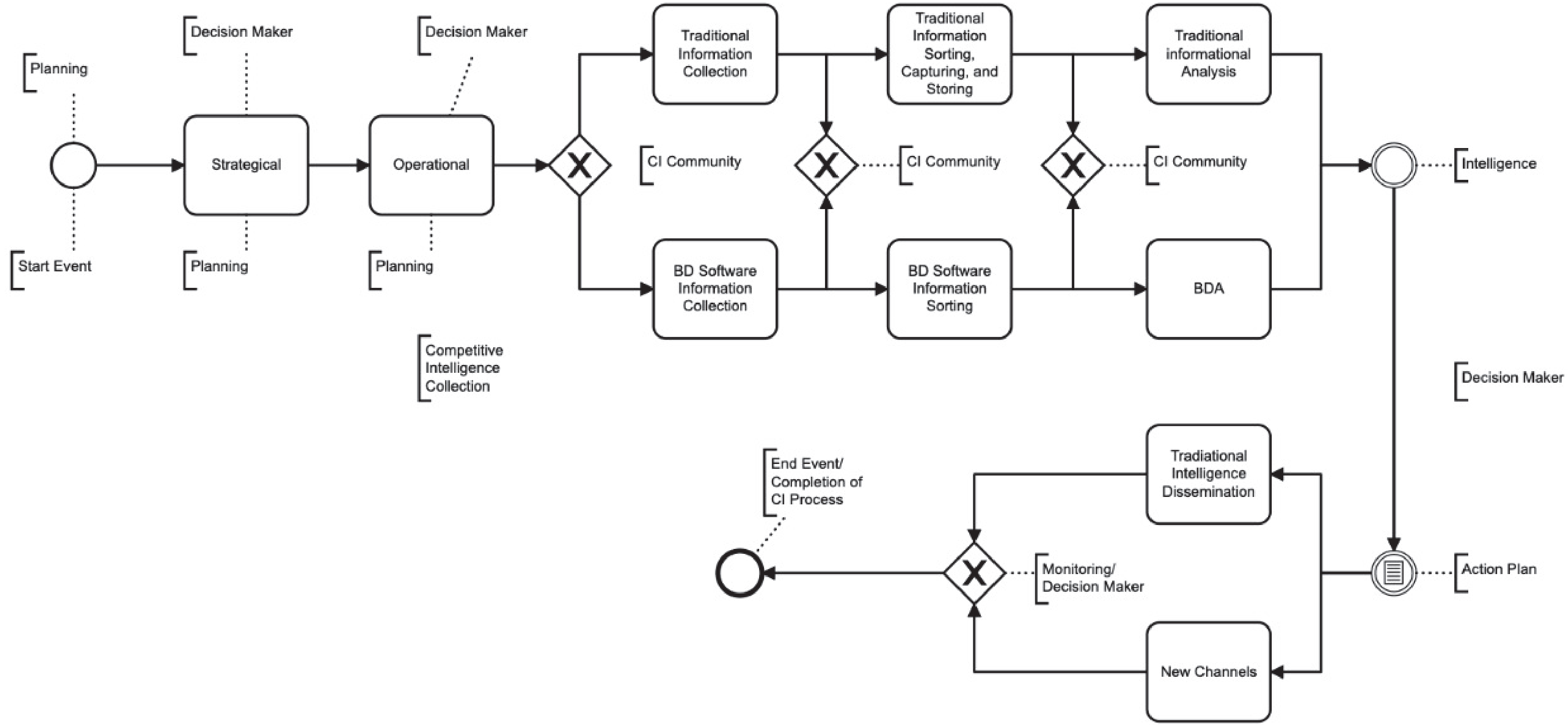

Figure 8 The proposed model (CCIP-BDABM) for this study

2.12 Chapter Summary

Contemporary businesses aspire to achieve competitive advantage through competitive intelligence approaches and have started to implement BDA to extract value for effective business decisions. Based on the discussion of the literature review, it is argued that organisations will benefit more from BDA solutions and accordingly the decision-making structure will be affected and enhanced. Accordingly, this study has found a chance to construct a model of both CI and BDA that is able to transform the process towards the desired business performance. Next Chapter outlines the methodology adopted for this study

Chapter 3 – Methodology

“If you know the enemy and know yourself, you need not fear the result of a hundred battles,” Sun Tzu writes. “If you know yourself but not the enemy, for every victory gained you will also suffer a defeat. If you know neither the enemy nor yourself, you will succumb in every battle.” Sun Tzu, by (McNeilly, 2011)

3.1 Introduction

The success of a study is, to a large extent, dependent on the methodological strength approach. The methodology is considered the research bedrock that lays a roadmap on how the research will be conducted (Bryman and Bell, 2018). It includes methods, approaches, strategies, tools, and the analytical designs that the research will seek to study the subject matter, and it all provides the study's actual contribution to the broader body of knowledge.

This section will thus move forth, addressing the methodological development of the research in hand, outlining philosophy, approaches to the conduct of the research, the research method and design, and the sampling strategy. For that, the research will adopt the research onion by scholars Saunders et al. (2007).

The interconnection development of research methodological layers provides a clear strategy and guidance on to conduct the research. The research onion model guides the research methodology and develops watertight research methods that help conduct objective investigations. Figure 9 is the symbolic representation of the research onion model for the current research methodology.

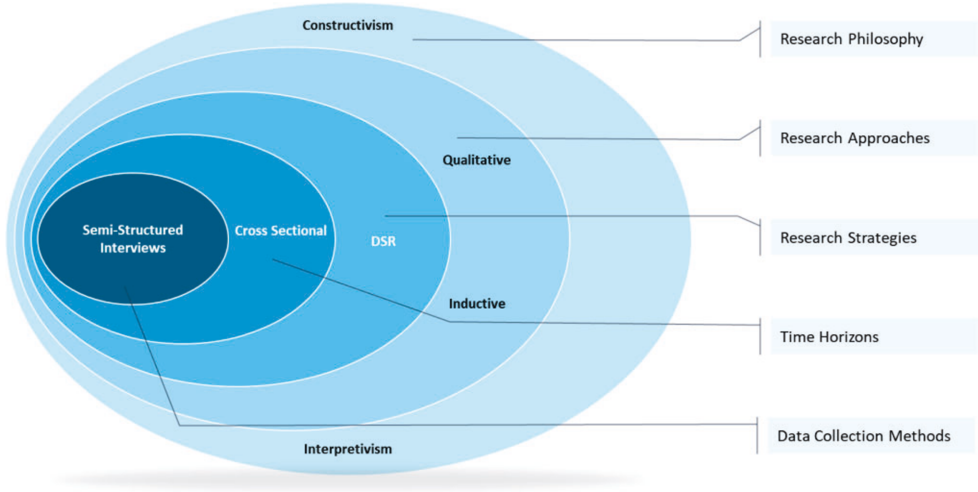

Figure 9 The contextualised Saunder’s research Onion for this study.

3.2 Research Philosophy

The research philosophy is the researcher's conviction about how the study should be approached, what type of data the research will seek to gather, and how (Saunders et al., 2007). Research philosophy occupies the outermost layer of the research onion; therefore, this implies that it is concerned with the way of knowing about the research subject.

The philosophy entails all the preliminary knowledge and conceptions of the researcher, which, accordingly, shape the other dimensions of the study (Rajasekar et al., 2013). It is determined based on the research questions and objectives, and this should ideally be in line with the type of data that the research seeks to gather. Since the research philosophy is the trajectory for the entire research and all other subsequent research selected parameters, this study is defined to follow the constructivism interpretivism philosophy approach, explained as below.

3.2.1 Constructivism

Constructivism philosophy emphasizes the role of human interaction and experience in the development and realisation of knowledge. Many constructivist perspectives and approaches make constructivism a wide philosophy in itself (Saunders et al., 2019;

Antwi and Hamza, 2015). Ontological constructivism accounts for knowledge manifest from human experiences, perspectives and conventional knowledge (Antwi and Hamza, 2015).

Social constructivism, which ideates rationale, is that knowledge can only be created through the interaction of people, and it is, therefore, more of a learning theory (Rajesakar et al., 2013). Proponents of social constructivism theory to knowledge development and gathering indicate that it is the underlying natural process of learning which can be seen between people and children (Rajesakar et al., 2013; Myers, 2008).

Also, psychological constructivism exists; it is a form of constructivism that investigates the human-based creation of meaningful systems guiding the understanding of knowledge and phenomena (Piaget, 1977). Worth mentioning, genetic epistemology (Piaget, 1977; Tsou, 2006) is another type of constructivism philosophy that concerns itself with studying the development of knowledge of its origins.

Other forms of research constructivism philosophy seek to underpin the origin and development of knowledge; However, the consensus among scholars of constructivism is that it consists of and seeks to study multiple versions of reality (Piaget, 1977; Myers, 2008; Rajesakar et al., 2013).

Since truth is created by experience (Piaget, 1977; Rosa et al., 2020; Silva, 2021), and considering this study's scope to explore the experiences of running competitive intelligence process, and what is the truth of a successful practice behind this process while implementing BDA, the researcher sought to use qualitative data collected from experts based on their experiences and knowledge and as such, the study applies constructivism philosophy.

3.2.2 Interpretivism

The interpretivism philosophy challenges realist and positivist views that the truth is existent in the environment independent of human conscience (Curry, 2020) and that the role of the researcher in research makes it bias. Interpretivism believes that without human involvement, there is no knowledge, and there is no truth in the environment (Klenke, 2016; Bryman and Bell, 2018). The approach promotes the researcher's participation and contribution to the study (Klenke, 2016). Opponents of this philosophy fault its subjective approach and opine that it breeds more bias based on the researcher personal opinion. However, collecting data through the most common method under interpretivism, interviews (Merriam, 2009), helps the researcher collect more information about a subject matter than can be gathered from surveys or observation (Miles, 2020). The social constructionist theories are deemed to follow the interpretive approach because it supports knowledge sharing and contributes to the growth and transfer of knowledge (Myers, 2008; Antwi and Hamza, 2015).

This study has followed the interpretivism philosophy to find out what truth means in the actual setting. Interacting with CI and BDA experts is vital, to collect unique life experiences and provide an eminent picture of reality by which our mental small world representation or model of reality is constructed (Maitland and Sammartino, 2015).

3.3 Research Approach and Techniques

This section presents a clear description of the approach and strategy selected based on the philosophies identified and adopted above. First and foremost, the research has developed a data collection instrument in the form of a semi-structured interview. The tool will be used to collect data based on explorative questions directed to the participants who are experts in their field of CI and BDA.

Therefore, the research approach will be inductive in nature, whereby the research will seek to analyse the descriptive data collected from the semi-structured interviews (Creswell, 2014) of different participants and derive meanings based on their statements and feedback.

The inductive research is helpful in a study of a particular area of knowledge where the purpose and objective of the researcher are to find a deficiency in existing theory and to come forth with theoretical conclusions that enhance the existing theory or present a new one (Woiceshyn and Daellenbach, 2018; Azungah, 2018). The inductive research approach is beneficial when conducting a qualitative study of social science; it allows the researcher to interrogate further while collecting data to gather more knowledge of the study (Mannan, 2020).

Merriam (2009) enlightens that the semi-structured interviews are distinguished from structured or open interviewing processes; it allows the researcher to be able to ask the same question to all participants in the research while providing room for the interviewer to probe any emergent lines of thoughts further (Mannan, 2020).

The semi-structured interviewing process has, in the recent past, developed significantly into a much appreciated and adaptable research strategy for multidisciplinary studies (McIntosh and Morse, 2015); it qualifies as a standalone research process, and it is unfettered with the dimensionalities of different philosophies (Husband, 2020).

Together with the above assertion, McIntosh and Morse (2015) highlight that, through semi-structured interviews, four major purposes of research can be attained – the first one is descriptive/corrective, second is descriptive/confirmative, third is descriptive/divergent, and the last one is descriptive/interpretive. The above four semi-structured interview purposes allow each participant to further contribute based on their knowledge and experience.

Young et al. (2018) recognises semi-structured interviews' advantages and claims that it is impossible to achieve the contribution to knowledge through a structured interview that is limited to the questions set, and it is hard to attain the same through an open-ended interview that does not have structure guidance of answers. Mannan (2020), in wrapping up the semi-structured interviews' advantages when compared to other interview methods, notes that the use of semi-structured interviews is adaptive to both quantitative and qualitative analysis while the other types of interview approaches can only qualify for qualitative analysis. The semi-structured interviews allow for the item-by-item analysis and comparison from one participant to another, which enables the attainment of the four major research purposes as outlined by McIntosh and Morse (2015).

Finally, scholars herein cited are in concordance that in research where the participants are experts or have relatively actual knowledge and experience of the subject matter in question, the semi-structured interview approach helps ascertain, confirm, critiquing and refute aspects of the body of knowledge in order to lead for better development and contribution (McIntosh and Morse, 2015; Young et al., 2018; Mannan, 2020).

Considering the premise of the current study, the selected participants are experts in CI and BDA from both corporate and academics settings. The practitioners are all decision makers with long years of experience related to the area of the study, and the academics are all involved in studying big data solutions and impact on organisational performance.

3.4 Research Time Horizon

As explained in the previous sub-field of this chapter, the research sought to roll out an interview as the only tool for data collection. Therefore, a mono-method of research will be adopted to enable the research to objectively pursue the research objectives while seeking to answer the questions raised from the research.

Two research timelines (Saunders et al., 2007) are expected in conventional research: longitudinal and cross-sectional. The longitudinal research timeline refers to research that focuses on a range of time, i.e., five years or ten years. On the other hand, cross-sectional research refers to research conducted at a specific point in time. The current study focuses on collecting data and analysing it at a specific time and therefore qualifies as a cross-sectional study.

3.5 Data Strategy

It is important to note that the data strategy of data collection and analysis is at the innermost part of the research onion because it is an integral part of the research methodology.

Saunders et al. (2007) inform that a study's data collection and analysis procedures have to be rigorous and unbiased if the research seeks to impact knowledge in a particular field. Therefore, this sub-field will report on the research's actual strategy to collect and analyse data, and the sampling approach of choosing participants.

3.5.1 Design Science Research

The researcher needs to define which methodological choices to proceed with that can best impact research findings to answer the research questions. The design science research (DSR) approach is adopted for this study as the strategical approach for discovering and identifying solutions and problems relevant to CI process while implementing BDA, and directly creating a new conceptual model, to address those problems and thus establish a link to the theoretical explanation that fills the research gap.

DSR *"is a research paradigm that answers questions relevant to human problems via the creation of innovative artefacts, thereby contributing new knowledge to the body of scientific evidence"* (Hevner and Chatterjee, 2010, p.5).

In order to comprehensively debunk design science research and promote the understanding of why it is integral to the current study, it is critical to understand its antecedents. Design science research is a branch of Information Systems (IS) research (Doyle et al., 2016); for the applicability in design while stimulating critical thinking (Benbasat and Zmud, 1999). Alturki and Gable (2014), in their detailed research on design science research, indicate that DSR is one of the phases of IS, while the other phase is behavioural science research.

Behavioural science research is addressed through the justification and development of theories aimed at explaining and providing predictions for phenomena related to the knowledge substance and/or aspect in question (Behavioural Sciences Editorial Office, 2021). While, on the other hand, the design science research of IS addresses the research substance through the development and examination of informational artefacts aimed at meeting a particular identified knowledge substance (Hevner et al., 2004; Morana et al., 2018).

Cartensen and Bernhard (2018) point out the need to conduct comprehensive research using behavioural and design phases to complete and attain Information Systems (IS) research. However, despite both phases of research are helpful for comprehensive Information Systems research, they differ as far as the goals are concerned, which means that each one of them can be applied individually depending on the researcher's goal (March and Smith, 1995).

The technological experience challenges the behavioural science study for the inability of the user to deeply engage with a working artefact (Sutton et al., 2021); It lacks engaging experience with functional systems as the user engagement with intelligent systems is based on their cognitive fit with the decision-making models (Arnold et al., 2004).

The root of design science research has focused on engineering and systems studies in general (Hevner et al., 2004); it was informed by the need to resolve problems in engineering and systems studies as well as practices to improve the knowledge of humans as far as the creation and innovation of artefacts or substances of knowledge are concerned (Bider et al., 2020). This implies that DSR enhances the interaction between humans and design knowledge to improve complex real-world problems using innovation (Hevner et al., 2004; Drechsler and Hevner, 2016).

Sustainability and innovativeness are deemed benefits of design science research (Becker et al., 2015; vom Brocke et al., 2013). The paradigm has witnessed a significant knowledge increase by providing a research model of problem identification and resolution for the innovative and technological aspects of the contemporary world (Watson et al., 2010).

This unique ability to integrate aspects of engineering and technology to promote knowledge extension has produced a room to design new innovative artefacts and substances of knowledge through the development of new models, constructs, and instantiations methods (Gregor and Henver, 2013). It develops a design through the development and interrogation of the arrangement, design and construct of things to visualise better options that can be used to achieve the set goals (Bider et al., 2020).

The utility of DSR in terms of knowledge capabilities is demonstrated through the ability to interrogate and promote the development of new design knowledge integrating IS with the organisational strategy (Gregor and Hevner, 2013; Bider et al., 2020). Becker et al. (2015) agrees with the above and add that design science research is instrumental in technology-based organisations as it helps in maximizing the utility of any technologies invested. These may include as much as the use of information technology to inform business practices.

Since the information systems can sustain business dynamic capabilities (Teece, 2007), IS practitioners need to align between information technology investments and subsequent information systems designs to promote a unified and productive infrastructural coalition (Henderson and Venkatraman, 1993).

To the above extent, information systems research must be open to the interlink between information infrastructure and business strategy. In fact, information technology has, in recent years, been at the core of business strategy and the organisational infrastructure; it allows to enhance the understanding of business operations between IS practitioners (Kalakota and Robinson, 2001; Carstensen and Bernhard, 2015).

Design science research is seemingly an engineering and systems-based approach; it can promote better visualisation in the organisation through the use, interrogation and improvement of technology. It promotes the development of novel solutions to design challenges that have led to DSR being adopted in many other fields and domains, including but not limited to architecture, economics, business and healthcare (Vom Brocke et al., 2020).

DSR models are found in the work of Takeda et al. (1990), Vaishnavi and Kuechler (2007), and Johannesson and Perjons (2012) which contain very similar process steps, knowledge and theory flows and outputs. Two models are found the most prominent DSR methods (Montasari, 2016) in relation to the information system domain (IS): Hevner et al. (2004) and Peffers et al. (2006).

3.5.1.1 Hevner’s DSR Model

In the design process, a number of activities are implemented sequentially to ensure that they lead to the production of a useful artefact (Carstensen and Bernhard, 2019). The produced artefact is then implemented to provide solution for the problem at hand. Hevner et al., (2004) provided seven DSR guidelines: 1. Design as an Artefact 2. Problem Relevance 3. Design Evaluation 4. Research Contribution 5. Research Rigor 6. Design as a Search Process 7. Communication of Research

Hevner's DSR activities present organisational and technical discipline that is technology proactive. It produces and evaluates innovative IT artefacts of an important task through integrating multiple activities that function seamlessly and effectively. The model supports a platonic view of the design practice, which continually interrogates the processes to find how suitable they are in promoting the development of the product (artefact) to support the resolution of the problem. Cartensen and Bernhard (2019) indicates that the above leads to building and evaluating an interim process that is returned several times and iterated until the final product helps resolve the identified problem.

Evaluating the product against the problem and its ability to resolve the problem is one of Hevner's DSR model's strong features (Bider et al., 2020); it is possible to effectively interrogate the design process and the artefact to come forth with necessary improvements.

Hevner's DSR approach insists that through the creative process of evaluation and examination of feedback between process and product, the evolution of the process must be kept in consideration by the system, determining the path of product development that can be used in informing future designs (Hevner, 2007).

Case and Light (2011) claims that Hevner's design science research model develops four artefacts: processes and instantiations, constructs, methods and models (artefacts). The artefacts are built to assist in resolving identified problems (Bider et al., 2020), while the definition of problems is identified as the constructs, because it involves the language for evaluating the problem and its solution space (Morana et al., 2018).

3.5.1.2 Peffer's DSRP Model

The performance of DSR projects has been based on several process models, such as Nunamaker and Chen (1991), Walls, Widmeyer, and El Sawy (1992), Hevner (2007), and Kuchler and Vaishnavi (2008). Peffers et al. (2006) DSR process model has combined elements of previous models, and thus it provides a graphical representation of carrying out and presenting the conceptual process of DSR (Montasari, 2016).

The design science research process (DSRP) model, includes six steps: problem identification and motivation, the definition of the objectives for a solution, design and development, demonstration, evaluation, and communication, with four possible entry points: problem-centred initiation, objective-centred solution, design and development-centred initiation, and client/context initiation. The objectives of (DSRP) approach are to be consistent with existing literature, provide a provision of comprehensive process model and evaluate DSR through a mental model for presenting and understanding the method (Montasari, 2016; Heathcote et al., 2020).

A brief description of each DSRP (Peffers et al., 2006) activity follows:

Activity 1. Problem identification and motivation. The first activity determines what is the research problem and explains the solution's value. grounding the value of a solution shall perform the following: motivation for the researcher and the audience of the research to strive for the solution and also, it provides appreciation for the researcher's understanding of the problem. Knowledge is required for both problem and solution.

Activity 2. Define the objectives for a solution. The objectives of a solution can be inferred from the problem definition and knowledge of what is possible and feasible. The objectives can be quantitative, e.g., terms in which a desirable solution would be better than current ones, or qualitative, i.e., a description of how a new artefact is expected to support solutions to problems addressed. The objectives should be inferred rationally from the problem specification.

Activity 3. Design and development. A conceptual artefact will be created; it can be any designed object in which a research contribution is embedded in the design. This activity includes determining the artefact's desired functionality and its architecture and then creating the actual artefact.

Activity 4. Demonstration. This activity demonstrates the use of the artefact to solve one or more instances of the problem. This could involve its use in experimentation, simulation, case study, proof, or other appropriate activity.

Activity 5. Evaluation. The evaluation measures how well the artefact supports a solution to the problem. This activity involves comparing the objectives of a solution to actual observed results from use of the artefact in context. Depending on the nature of the problem venue and the artefact, evaluation could take many forms. At the end of this activity the researchers can decide whether to iterate back to step three to try to improve the effectiveness of the artefact or to continue on to communication and leave further improvement to subsequent projects.

Activity 6. Communication. Here all aspects of the problem and the designed artefact are communicated to the relevant stakeholders. Appropriate forms of communication are employed depending upon the research goals and the audience, such as practicing professionals.

The six DSRP activities (Peffers et al., 2006) is consistent with prior DSR models (Wall et al., 1992; Takeda et al., 1990; Rossi and Sein, 2003; Archer, 1984; Eekel and Roozenburg, 1991; Hevner et al., 2004), as well as it provides a clear mental model with a nominal process which allows a researcher to carry out DSR to answer research questions. Therefore, Peffers et al's DSRP roadmap will be followed for this study to produce a high-quality artefact that would be accepted as valuable, rigorous and publishable within the field of marketing.

3.5.2.3 Limitation of DSR in this study

Despite the fact that DSR appears appropriate for this study where the entire investigative process needs to be followed, the time limitations have demonstrated a challenge for the researcher; each phase of an iterative cycle with each participant had required a considerable time to transcribe, anonymise and analyse the interviewee answers. Transcribing and analysing participants' interviews had to be repeated four times until being able to get a consent from all participants on final model. For that, a job tracker has been created to allow the researcher to organise and follow up on jobs related to each interview within the iterative cycle.

Moreover, there has been a limitation to the number of participants agreed to participate in this research, especially for the fact that they have been informed of iterative cycles of interviews required. Therefore, the communication part prior confirming the final number of participants have consumed along period of time until it has been finalized. Besides, engaging participants throughout the research journey of iterative interviews and feedback of each cycle has demonstrated a challenge, rather than a limitation.

Also, since this research follows an interpretivist approach integrating human interest into the research scope, it was important for the researcher, as a social actor, to appreciate differences between results and to subside any room of bias.

3.6 Sampling and Data Collection

According to the research purpose, the sampling approach is defined (Myers, 2009). sampling is critical because it holds on to data sources that provide answers for the research questions (Patton, 1990).

Multiple sampling approaches can be obtained to serve different purposes. According to the type of data required, the sample of the population can be defined (Merriam, 2009). Sampling approaches, generally, can be categorised broadly into two types: probability and non-probability sampling approaches (Bajpai, 2011; Myers, 2009; Morse, 1991). Bajpai (2011) indicates that the underline criterion is by deciding if it is randomly to select the sample of data collection or not.

Some of the probability approaches include stratified sampling, systematic sampling, cluster sampling and simple random sampling (Ames et al., 2019). Bajpai (2011) elucidates that even though these methods are popular in research, especially research dealing with big populations, the risk of bias entailed is high due to the lack of specificity in their targeting, or because it is a broad-based approach to targeting. On the other hand, the non-probability sampling category uses a select sample to represent a larger population (Patton, 1990; Crowther and Lancaster, 2008). It contains several sampling approaches aiming to select a group to represent a larger population. Wilson (2008) clarifies this approach by adding that in most of the cases where this approach is used, the researchers usually seek to gather specific information from a specific group of people. This information is unlikely to be held by everybody in the general population, and therefore, pursuing a select few of the people who may be privy to the targeted information becomes useful (Ames et al., 2019).

In non-probability sampling, members of a population do not have the same opportunity to participate in research; this remains one of the main differences between probability and non-probability sampling techniques (Tansey, 2007). The non-probability genre includes convenience sampling, purposive sampling, quota sampling, and snowball sampling (Bajpai, 2011).

Purposeful sampling attempts to select research participants according to criteria determined by the research purpose. This type tends to be used in qualitative research (Merriam, 2009; Collins et al., 2006). Because the purposive sampling approach is useful to research that seeks to judge participants' fitness based on the information they can provide, answering the research question (Crowther and Lancaster, 2008), this study and subject to the sampling types gathered, will peruse with the purposive approach of non-probability sampling as it is the most relevant.

In most cases, the selected population have a particular level of knowledge or information access (Raina, 2015) that would be useful for the research, and therefore the research only needs their exclusive participation.

3.6.1 Data Analysis

The qualitative data analysis software Nvivo12 was used to support manual qualitative analysis. The coding using manual tools like sticky notes and colours markers, combined with the digital software, has helped in managing and analysing interview results. The partial support offered by Nvivo primarily includes coding data, linking between results and finding out common themes.

3.6.2 Participants Profiles

For this study, seven real estate organisations that are medium to large-sized and aggressive in marketing campaigns were targeted. The same for universities; six universities in UAE were listed and approached as well.

All participants were approached primarily through LinkedIn[4]; it has allowed the researcher to search for certain profiles that can help answer the research questions. The purposely selected participants have all received an invitation to participate in this study. Out of 34 profiles, that have been contacted, only 10 profiles have responded and agreed to participate in this study. Later, two profiles have withdrawn their participation due to time constrain reasons.

Participants from the practice corporate settings (practitioners) have all a common criteria of high managerial level that is involved in decision-making, and all has experience of managing CI through the implementation of BDA.

4 LinkedIn is the world's largest professional network on the internet. Source (www.linkedin.com)

Participants from the academic setting (academics) are all currently teaching and researching technological solutions that impact the organisation's performance, including BDA. Table (3) lists the participants' profiles of this study

Table 3 Participants' Profile List for this study

Practitioners			
Pseudonym	**Position**	**years of experience**	**years of experience in real estate**
Participant A	Marketing Manager	21	14
Participant B	COO	27	10
Participant C	Marketing Manager	18	9
Participant D	CEO	34	22
Participant E	Digital Marketing Manager	15	11
Academics			
Pseudonym	**Position**	**years of experience**	**Degree**
Academic A	Asst. Professor	15	Doctor of philosophy, PhD , Information systems
Academic B	Professor	18	Doctor of philosophy, PhD , Computer Software Engineering
Academic C	Associate Professor	21	Doctor of philosophy, PhD , Wireless and communication systems

3.7 Reflexivity

At its core, the qualitative research approach provides content that is useful for practical applications (Creswell and Poth, 2018), and it enables researchers to gain an accurate understanding of a topic. However, qualitative researchers often engage in exploring their positionality and understand how it constructs their knowledge. This positionality can be explored through the use of reflexivity (Swaminathan & Mulvihill, 2018).

Roulston (2010) defined reflexivity in research as “the researcher’s ability to be able to self-consciously refer to him or herself concerning the production of knowledge about research topics” (p. 116)

Typically, reflexivity involves examining our judgments, practices, and belief systems during the data collection process. The goal of being reflexive is to identify any personal beliefs that may have incidentally affected the research. According to Haynes (2012) reflexivity represent the researcher’s role in being aware during the research project, acknowledging ways in which the researcher is influenced by the object of the research, which can affect both the research process and findings.

For this research project, the researcher was prepared to question her own assumptions as it is an integral role in the data collection process, especially during the iterative interview cycles. The researcher was aware that there are countless ways of bias may affect the study, therefore, it was important to continue questioning her own voice during the data collection and analysis and ensuring to remain neutral so she can absorb other opinions.

Moreover, documenting answers, keeping track of the iterative process, and leaving coloured notes that could be retraced later if answers needed to be revisited, have all demonstrated reflexivity throughout the iterative interviews cycles to make sure all opinions and feedback are covered, and none have been avoided. Worth mentioning that memos helped the researcher to guard against forgetting or distorting what took place in earlier stages of the project and served as a reminder to keep an open mind. Also, some questions helped the researcher to periodically engage in the process of reflexivity, like “What do I know? How did I know that? What do I do with what I have found?”

Therefore, reflexivity is cited as an important tool for enhancing the rigour and trustworthiness of a qualitative study (Shelton and Flint, 2019; Merriam and Tisdell, 2016). It is often referred to as the tests of validity, which can justify the claim to knowledge.

3.8 Chapter Summary

This chapter has presented and justified the research methodology adopted for this study to develop conceptual solutions that meet the needs of the problems identified in the domain. The chapter refined the process involved in the theoretical groundwork related to adopting the research philosophies, strategy, sampling, data collection and analysis techniques, and designing and evaluating solutions with appropriate justifications.

Figure (10) demonstrates a methodological structure summary that entails the methodological process undertaken for this study. Based on the philosophical research standpoint and research aims and objectives, the selected DSR mental model started by identifying the research problem and define objectives of a solution. Artefact demonstration was applied through iterative interviews, which had deployed evaluation at each time. Hereafter, the data communication and dissemination are intended accordingly. Next Chapter outlines findings and critical discussion.

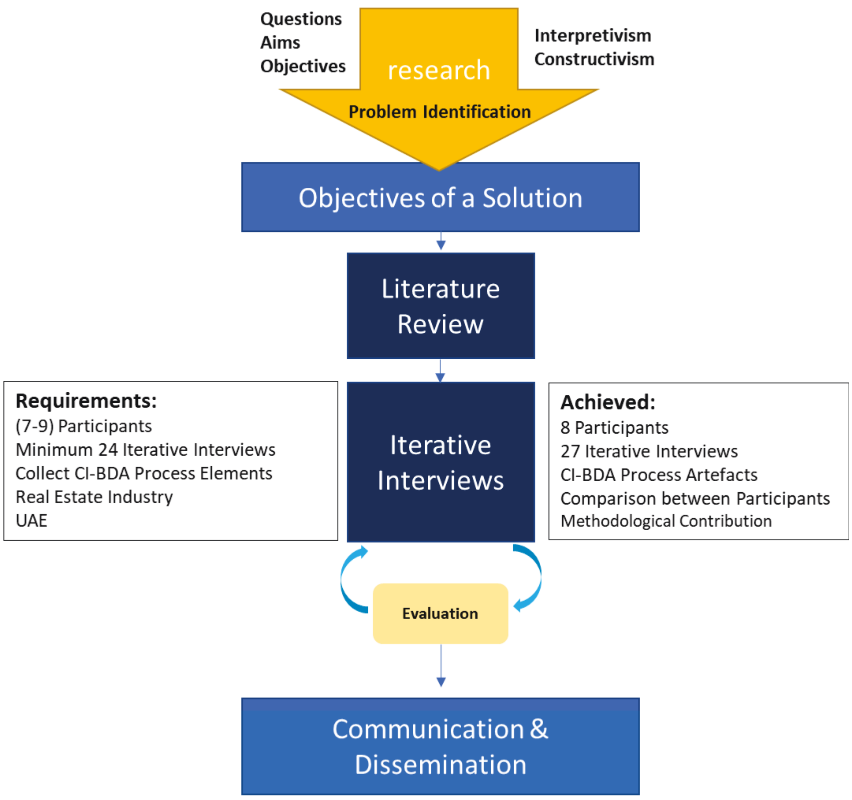

Figure 10 Current study's methodological approach

Chapter 4 –Findings and Discussion

This chapter presents qualitative research findings that had utilised the DSR method to answer the research questions. The main focus of this study was to understand how the competitive intelligence process runs while implementing BDA, confirming on the actual influential factors for CI decision-makers.

Since participants are experts from corporate and academic settings, the findings are presented in two parts; the first is based on findings from the practitioners' interview results, and the second is based on findings from the academics' interview results.

Data collection was conducted through iterative interviews, to the point that no further feedback, comment, or relationship between process elements is required. Since questions were guided by the proposed CCIP-BDABM model, the results will carry on the same sequence from starting the CI project until completion.

This section will next demonstrate gap analysis to compare between findings from practitioners' and academics' interview results, followed by a critical discussion section.

4.1 Findings from Practitioners' Feedback

The conceptualized (proposed) CCIP-BDABM was shared with the selected experts, referred to as "practitioners", who practice CI / BDA in corporate real estate firms to obtain their views on the developed model.

It was found that launching Competitive Intelligence in corporate settings is more complicated than simply planning to start it. This study finds that profit motivation stimulates organisational activities. However, profitable growth requires significant skills management through periodic justifications and modifications. Interview results confirm that practitioners seek to develop an efficient analytical tool, enabling them to choose the right direction and decisions to achieve their goals.

4.1.1 Iteration 1

This section discusses practitioners' initial feedback on the proposed CCIP-BDABM, which demonstrates phases of intelligence creation until delivering messages of competitive advantage to the target customers. The headings under this section were informed by the discussions that took place throughout the interviews.

4.1.1.1 Planning for CI- CI need

The first activity in the proposed CI model is *planning*. The interview questions aimed to investigate this first activity to understand it from a practical point of view. The interviewed practitioners explained the *planning* step from angles slightly dissimilar to the proposed CI process. Going back to the research problem, these differences were expected since a comprehensive model encompassing the CI process does not exist while utilising BDA. Thus, processing CI is conceptualised within the academic literature by using traditional marketing tools (Sanjay and Nishant, 2015; Aljumah et al., 2021). For instance, assigning a team to collect competitors' analysis through market visits or collect market trend reports from sales representatives.

Despite the fact that the planning phase is commonly identified in several CI models in the literature (Cruywagen, 2002; Kahaner, 1996; Bose, 2008; SCIP, 2007; Calof and Wright, 2008; Sawka and Hohhof, 2008; Pellissier and Nenzhelele, 2013), it is not identified the same way in corporate settings. Noticeably, practitioners were sceptical and paused a few moments before answering the question: "Do you agree that the competitive intelligence process starts with planning?". It was clear that planning is more complicated than what the model has proposed

Interview findings reveal that the *planning* phase was consolidated by identifying CI's *need* rather than discussing how to plan for it. This is not to imply that *planning* is not an essential element for the CI program. Quite to the contrary, *planning* is found to be a crucial subject for the process; nevertheless, it is embedded within another two phases of the CI process, as shown in (Figure 11) of the first draft model.

Figure 11 CI "planning" allocation within the first draft model

Discussing the CI *need* has helped solicit more views on how organisations launch the CI program. Some practitioners explained the *need* through a product-oriented strategy, i.e., introducing a new property project with well-defined positioning for its consumer target. In this case, and to achieve business success for the organisation, it is *needed* to target that particular category of customers aiming to sell them units of this project. Another strategy was found that explains the *need* identification of CI, and it is purely customer-oriented, i.e., focusing on retaining current customers.

"Buying properties in the UAE, particularly in Dubai, is a very attractive thing for both residents and tourists. It is a country that people want to invest in or live in or even have a place for their holiday. So, there is a big chance that a customer who already purchased property will purchase again." Practitioner B said.

Word of mouth is a marketing term that was and still is a point of interest for marketers (Siqueira et al., 2020). As per NVivo analysis (Appendix D), one practitioner stressed the need to create messages, which holds a competitive advantage value, to communicate with current customers, where next they will communicate this message to others too. This practitioner claims it will enhance customer satisfaction. For example, sending birthday wishes, special promotions, or free service coupons; these tools will keep customers bonded and interested in talking about the business. Amid this atmosphere of customer satisfaction, most practitioners expressed that it implies higher chances of achieving sales too.

The interview results have provided a primary overarching regulator of the competitive intelligence need. Practitioners recognise that identifying the current organisational decision-making structure is essential to touch upon the need for CI. While seeking to determine the existing decision-making structure of the current organisations within this study context, it was found (Figure 12) that all of them implement a vertical management structure. It was clear that the management hierarchy in medium to large organisations is very well defined, and the HR role is clear and provides responsibilities and reporting panel for each employee. All practitioners appeared to acknowledge each employee's responsibilities and reporting channels while being discussed.

However, the CI *need* is not a one-person decision. It is produced throughout any of the management's levels. According to the business environment and situation, the *need* is endorsed by higher or lower managerial levels, and it can be circulated from the top-down or down-top. If CI need is found valid, then process can continue further.

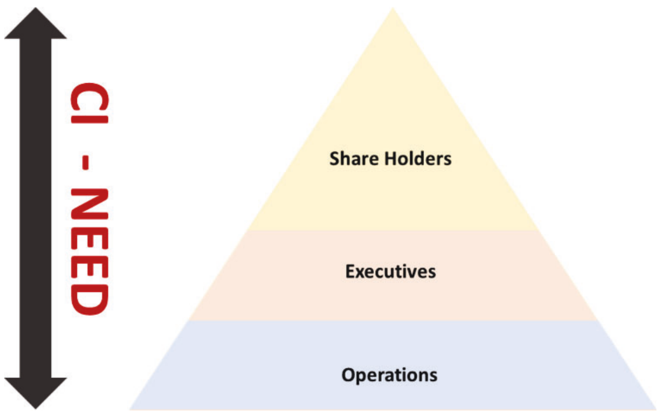

Figure 12 CI need produced in Vertical Management Structure, based on feedback from practitioners

4.1.1.2 Data Strategy and Data Architect

The interviews reveal that solid data architecture is important for the success of any data initiative. Practitioners expressed that they seek to understand the business IT infrastructure and the underpinning agility towards their data management. It seems that organisations in favour of big data utilisation have opened the door to data architects to establish a data solution modeling to secure their investment. The result matches the discussion in the literature review, which had touched upon organisational agility and dynamic capabilities, to explore when and how the business model can demonstrate IT and data solutions that help competitive intelligence activity.

However, in the proposed model, data strategy and data architect were not employed as one of the main elements within the CI process. Previous studies of CI have identified the term *Data* from the perspective of a set of certain sequential phases that can achieve competitive intelligence; collection, capturing, sorting, storing, analysing and dissemination. The *data* management is part of BI team responsibilities (Inmon et al., 2019), therefore, it was expected that data strategy is not part of the marketing role of activities, and having said that, it is also not part of CI main elements of the CI process.

Remarkably, it is found that marketing experts (practitioners) are acknowledged and partially involved in data strategy (Figure 13). Two practitioners who are decision-makers in the marketing department both started the discussion of data strategy before coming to the main subject of competitive intelligence. Apparently, the marketing structure is changing, and some roles are now overlapping with another department, out of necessity and due to the importance acquired for marketing outputs and results.

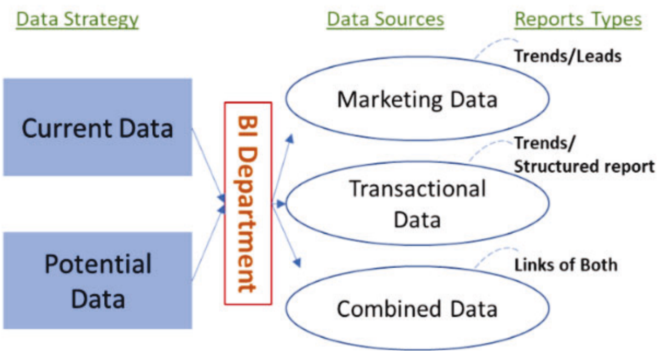

Figure 13 The proposed allocation of data strategy within the first draft model of CI process

The majority of practitioners clarified how the organisation arranges for periodic orientation seminars, conducted by the BI department or by the software provider, training top management, marketing, and IT teams on the data management process. Practitioner C said, *"It is in our calendar, and we call it big data training".* Attaining knowledge of data management varied with practitioner A, who claimed that data management knowledge is acquired from the BI department through direct communication with them.

It is found that clear data architecture is the foundation of how and when to implement a data strategy. The findings of this study indicate that BDA is strongly influenced by how management understands the role of data. Therefore, it was necessary to summarise the two main data pillars, discussed by practitioners, for the organisational data architecture:

1. Current data: includes all customers who have purchased or customers who have submitted their details through any channel of communication with the organisation, like the organisation's website.
2. Potential data: a data base of customers that the organisation can get either by approaching customers, aiming to receive back from them, or through big data software.

Practitioner B claimed explicitly: "*you are in complete chaos if you don't know which type of data to proceed with, and your management will lose interest in your project, thus it will lead to an assured failure".*

Data strategy was clear while practitioners discussed how organisations create the customer's need to buy properties in the UAE. The practitioners exemplified two cases of need creations; first, the business targets to sell, retain, and satisfy current customers for the reason of being a profitable customer. Second is when the business aims to gain new customers, increase market share, or enhance sales and revenue. The latter is achieved through approaching new potential customers.

Moreover, the findings reveal three data sources (Figure 14) that can be extracted from the two data collection pillars; marketing, transactional, and combined data.

4.1.1.3 Data sources

1. Marketing data: trends and leads that are extracted from digital marketing campaigns, like Facebook, Google, Instagram. This information provides a holistic view and feedback behind each campaign and gives insight into customer behaviour and interaction with the campaign. It does not provide private information like an email address or mobile number; it converses only certain demographic characteristics.

2. Transactional data: this is the personal information of customers who have interacted with the organisation through any transaction ticket, contract or filling a form. It can be collected through purchase or rental contract, purchase and rental

interest forms, (Q & A) forms, business card collection bowl, and, also, it can be through website interaction where customers fill and submit their details voluntarily. Usually, this data appears in a structured format like in Excel sheets.

3. Combined data: this is a previously analysed data that has a mix of marketing and transactional sources, combined together to give links between trends and customer information, i.e., linking social media campaigns to the website will allow the organisation to identify each customer/user.

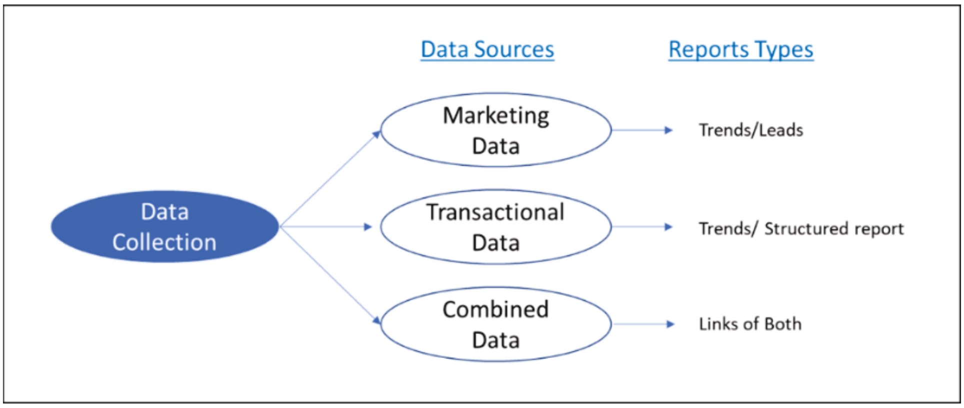

Figure 14 Data sources and data types extracted from data collection pillars

4.1.1.4 Data Collection, Storing, Sorting, and Analysis.

The findings reveal that traditional marketing tools were demonstrated in the organisations before as propositional instruments for gaining competitive intelligence as opposed to the currently used BDA, which provides automated procedures for competitive knowledge. This section will list the several phases listed by practitioners, which explains the process of attempting to make data meaningful and turn it into actionable information.

Data Collection and Storing:

"The volume, variety and velocity of data are so much greater as it deserves the title BIG DATA" said practitioner A. At this level, all practitioners concur that the BI department collects data from the three types of sources identified in Figure (14).

Opinions differed as to which source of data collection is more valuable for organisational competitive intelligence. The majority of those who responded to evaluate data sources felt that social media is a dominating source that reflects insights into customers' behaviour. It is found that social networks like Facebook, LinkedIn and Twitter contain valuable data on customers' brand preferences, shopping patterns, interaction and feedback loops, sentiments and social communication topics. Such is reported, by practitioners, that it allows the organisation to gain timely and extensive insight into consumers.

While no practitioner doubted that social media is an essential source of big data collection, two practitioners expressed that transactional data is critical to business success. Online login, online purchase and online inquiry are reported to hold profitable customers for the business. These views surfaced in respect of successful decision-making, as some practitioners believe that profitable business is when competitive intelligence provides insight into current and historical customers who are considered part of the transactional database source.

Another data source was discussed, which links social media (marketing) and transactional data. Some transactional data, i.e., name and contact number, if combined with digital behaviour analysis of the same customer, can be an additional value-added for the marketing campaigns. It allows targeting each customer with personalised messages based on their reported preferences. Despite the difference in prioritising the importance of this source type, all practitioners found it to be a helpful type of data.

> "Transactional data is the primary source of the profitable customer; our customers' communication through our website is extremely valuable. If we receive 100 messages from customers looking for a 3-bedroom apartment, 70 messages looking for a 2-bedroom villa, and 20 messages requesting prices for a studio, accordingly we first prioritise our marketing campaign directions towards 3 bedroom apartments as the main product. Next, we can get support from social media for a similar customer demographic category. For sure, the campaign results should be more effective on revenue than a campaign based only on customers' online behaviour*".* Practitioner G explained.

Several issues were identified for the combined data type. Most practitioners' concerns regarding collecting combined data are summarised, regardless of their evaluation of which data source is more important.

1. Data accuracy
2. Data analyst proficiency
3. The selection of dimensions
4. Time convergence

Collecting data from data sources requires adequate technology and tools. It is found that the data collection techniques vary between IoT ecosystems, point of sale software, business partnership with data provider agencies, social media reports and mobile applications. As stated by most practitioners, a data scientist role (figure 15) evolves around the ability to extract the data from its original source, transform data for a clean and normalised form of information, remove redundancy, and load it into a database, warehouse or data lake that can be available and ready for usage. In this stage, the data management team must examine and fulfil additional concerns and needs, such as guaranteeing the data reliability and preparing it for use.

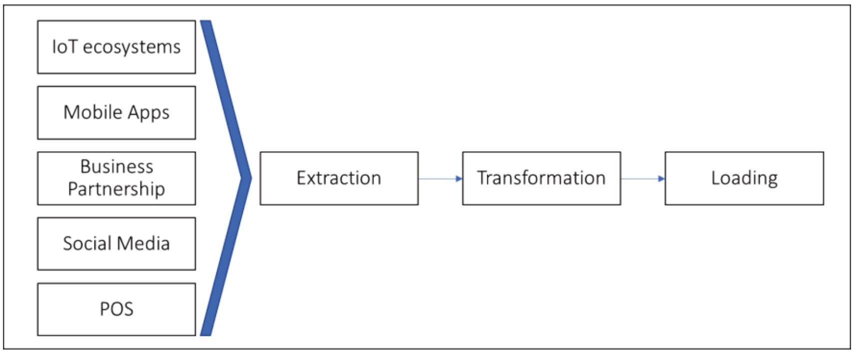

Figure 15 Data scientist role after utilising the data collection techniques

There was a sense of necessity for cloud data storage amongst practitioners stemming from concerns around the large volumes of data collected. Practitioners were familiar with big data structure. They seemed aware of organisation's actual data volume; images, videos, social media, and Google reviews. One practitioner, when asked about data storage, expressed that the human mind cannot imagine how much physical storage is required for this amount of data, and this is a reason to consider *cloud* as a logical solution for data storage.

Data sorting

Practitioners touched upon the difference before and after big data; previously, the amount of customer information was minimal compared to what is currently used. The majority reported that they feel challenged by the fact that data warehousing is increasing every day without fail. Practitioner A said: "as we go, we are storing more data about users, and it is becoming hard to decide what you want to do with it. How much I can automate for a marketing project, and how much I can utilise in my marketing campaigns".

The interview results report that data sorting is required in this phase using programming software that allows for the distributed processing of large data sets across clusters of computers.
The research finds that it is a concern if the organisation is new to big data. According to all practitioners (Figure 16), the challenge persists in choosing the right tool and software to process this large amount of data. Making this choice is a challenge; each software has its own process and packages. Software selection appeared in most interviews as a decision taken by the head of Business Intelligence. One practitioner said it is a top management decision, while another practitioner said it is a decision taken by both top management and the head of business intelligence.

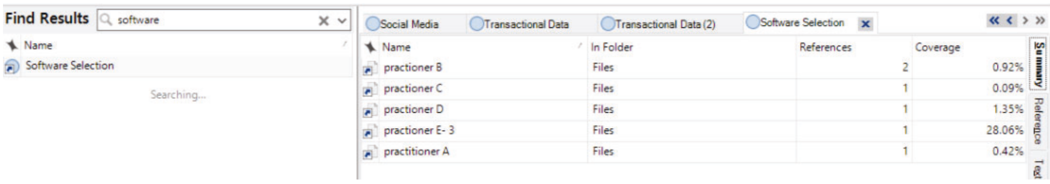

Figure 16 Coding of Software selection challenge appear in all practitioners results as per Nvivo analysis

Two discrete solutions to operate big data emerged from the discussion of newly adaptor organisations. First, is the in-house operation of BD software. The second is to hire a third party to do the job. Each direction is reported to have its pros and cons. In-house operation requires HR hiring that goes through standards and budgeting. The external party, which is the expensive choice, gives efficient results for the short term only, by which time, there is a higher chance the third party will lose interest in the project later.

Practitioners were asked to suggest other concerns, if existing, regarding the data sorting phase. Two practitioners expressed that data mismatch is a critical element that needs to be continuously observed, and one employee should be assigned to manage data errors and mismatches for all data records across the different platforms.

Data analysis

Practitioners reported that the data analyst is in charge of the data analysis phase throughout the CI process. Some practitioners argued that marketing decision-makers are involved with data analysts in the overall process, while others have shown less priority in observing the data analysts' jobs. The common view amongst practitioners was that the marketing goal is the main concern; data analysis reports must optimise the marketing strategy, including tactics that concerns the marketing mix.

The majority of practitioners have come across the term Data Visualisation during the discussion of Data Analytics. They expressed that despite their profound knowledge of big data and big data processes, they still need to have this type of intelligence visualised to make faster decisions. They need to extract factors affecting customer behaviour, customer satisfaction, competitors, product strength and weaknesses. Another practitioner echoed this view and said that visualised intelligence would make data memorable for marketers, decision-makers, and shareholders.

One practitioner reported that organisations are favouring the expectation of machine learning algorithms. It is found that shareholders are keen to explore the new trend of big data utilisation, which can perceive insights about their competitive environment from masses of data. For this subject of the organisation's investment in big data, the practitioners, on the whole, demonstrated a serious concern about organisations who invest in big data technology, considering it as a trend venture rather than a needed technology.

The sense of this concern is because big data rests on a considerable amount of financial and human resource investment. Additionally, the work involved in big data is laborious and time-consuming from the moment data is collected until it provides insight. It is not a one-person show; on the contrary, it requires a team of experts to run the software efficiently and working in harmony between team members is a must.

Two practitioners indicated that data analysts need top management support because their job requires powerful computer hardware supported by powerful software to sort, visualise and store data. The top management has to govern the process quality, or else, insights are not necessarily accurate.

In the events surrounding data analytics, practitioners also discussed that organisations tend to set dashboards that link between analytics and the key performance indicators (KPI's). These dashboards can be either before marketing campaign implementation or after, i.e., Facebook tracking metrics for marketing campaigns: open rate, likes rate, shares rate.

4.1.1.5 Data Automation

According to the findings, the data automation has been added to the draft model of CI process. This phase enables marketers to automate marketing activities using big data technology across multiple digital channels. It can also support the workflow by applying campaign customisation of a particular segment or particular channel.

Data automation came into practice after marketers found it challenging to download Excel sheets of customers' data. Marketers, according to practitioners, can plug in their sorted data, including social media and Google advertising, into Customer Data Platforms (CDP), creating automated design campaigns.

Practitioners justified the importance of marketing data automation differently. *Existing customers* and *new customers* are two common topics that all practitioners have focused on for data automation. They claim that it is essential to automate campaigns to satisfy customers onboard and automate other campaigns targeting new and potential customers.

Also, *increasing engagements* is another reason found for data automation. For example, practitioner C said: "*automated email campaigns that are informative about the product offering will drive immediate responses and engagement if the customer becomes educated or familiar about the product*". Also, practitioner A mentioned that "*Scheduled automated messages that are sent in response to a customer's activity will guide to more interactions that will lead to the purchase process."*

The findings reveal that the data automation workflow has a different timeline. Some automation can be on an annual calendar like birthday, cultural and religious occasions. Alternatively, it is a strategic automated interaction with the customer, for example, receiving promotional emails after several registered interactions from the customer. Additionally, the decision-maker can choose specific demographic criteria for each automated segment. According to practitioner B, the main reason for differentiating between segments is that in the UAE not all nationalities can purchase in particular areas that are restricted to locals.

"Automated messages sent to customers after completing a sales transaction, in my opinion, will get back to you with double the sales. You tighten the emotional factor with the customer, increase happiness after the purchase, and most importantly,

word of mouth will get you their friends added to your potential customers list". Said practitioner E.

Most of the practitioners showed concern about choosing the right customer for the automated marketing campaigns. They explained how their decision-making effectiveness relies on data accuracy. Therefore, identifying errors is a critical task for data architects while transferring data from its origin to the data warehouse, where all data analysis will take over.

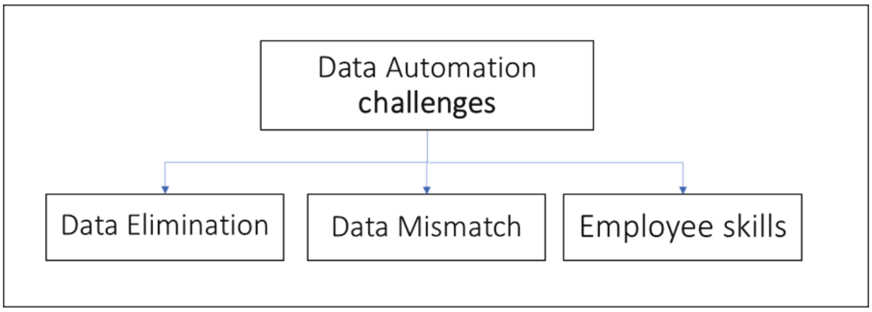

Figure 17 Data automation challenges for decision-makers

While attempting to investigate further into decision-making challenges during the phase of data automation. Three factors were identified (Figure 17) from the interview answers demonstrating decision-making challenges. First is data elimination; despite data being provided in a clear and normalised format, it still contains a large volume of customer lists that need to be eliminated according to decision-maker directions. The second challenge involves data mismatch issues, which can appear from mistakes in linking data from different sources or erroring data from its origin.

Practitioner D has another point of view regarding the obstacle; "*If you hire the right candidate, they will bring back the job correctly".* The feedback emphasises the importance of employee skills and the selection of their qualifications.

4.1.1.6 Marketing Reporting and Decisions

The possession of knowledge resources, formed by BDA, enables an organisation to reconfigure its resources and build dynamic capabilities (Côrte-Real, et al., 2017). The big data utilisation ability is hypothesised to embrace reporting systems using the potential intelligence to obtain competitiveness in a dynamic market context. In this section, the findings reveal interview feedback related to the marketing reporting structure based on big data utilisation.

It is important to mention that the marketing reports take place in the new draft model, as the first activity solely within the marketing department (Figure 18). Before this, BDA was completed and has provided the *needed* intelligence. Intelligence was used first to provide prescriptive reports supporting data automation (as explained in the previous section) and next for marketing reports.

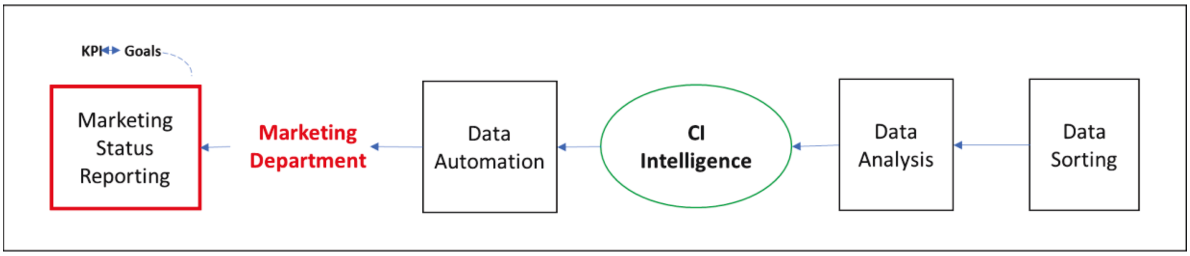

Figure 18 List of CI activities that led to the Marketing Status Reporting

Status Reporting

An initial review of improved decision-making through quantifiable and translucent reports showed a more significant impact and valuable insights if big data technology is utilised (Boyd and Crawford, 2012). Practitioners in this research showed confidence in intelligence based on BDA. Research results confirm that BDA has a beneficial impact on improved decision-making. Prompt questions aiming to understand practitioners' satisfaction level at the time of receiving BDA reports (the intelligence) and the findings reveal that all practitioners showed happiness and a high level of satisfaction in this regard. Practitioner A clearly explained "*having big data validated and available means I cannot simply neglect it, I haven't nor will I, actually I am the one now who believes in and pushes for the use of big data and I truly enjoy it".*

Hereafter, while aiming to allocate the first activity for decision-makers within the marketing department, the research results confirm that descriptive reports dominate at this stage of the CI process. Although the results are not quantifiable as Michael Wu claims that it reaches 80% of business analytics (Jeff, 2013), this research findings confirm that descriptive analytics (Sivarajah et al, 2017) are a primary first report type used by the marketing department after receiving the intelligence.

Defining the current state of business is what the marketing decision-makers need to do. Comparing KPI's to goals is expected by top management. "*Top management seeks to create a relationship between the spend and the generated revenue, the expectation of this relationship depends on the goal of each particular campaign"* said practitioner B. The marketing decision-maker is responsible for creating this status report using descriptive analytics and comparing it to the business objectives and goals. At this level of the CI process, both marketing and top management decision-makers are involved. Marketing directions rely on their feedback on the status report. All marketing activities are set behind this level, waiting for approvals.

It appears that the competitive environment requires a winning formula to enable the organisation to earn a return on its investment. The literature review suggests several elements composing the competitive environment: demographics, economy, other industries, technology, distributors, customers, substitutes, suppliers, government and industry regulators, prospects, culture, competitors, and unexpected circumstances (Sharp, 2009; Iwu-James et al., 2020; sewdass, 2012).

The research found a few topics related to the competitive environment that top management must discuss through the status report. Revenue, RoI, competition, economy, market share, agents and brokers are the most common topics extracted from practitioners' discussion.

Decision-Maker

As found previously in status reporting section, top management looks from a holistic point of view, checking on campaigns' achievement and how clearly, concisely and numerically it has been reported. However, findings also reveal that top management recognises marketing decision-makers characteristics as either *spenders* or *value creators*. One practitioner explained that value creation means working towards customers' satisfaction and, at the same time, meeting top management's expectations. In addition to the value creation characteristic for the marketing decision-maker, majority of practitioners discussed that knowledge about BD technology is essential to demonstrate successful decision-making.

Worth mentioning, practitioners were observed, during the interviews, to be knowledgeable about the big data process, software, reports and impact. Practitioners' analytical and communication skills appeared excellent; they articulate discussion very clearly and demonstrate confidence. Practitioner A articulate the importance of being a team player. Also, the findings reveal that decision-makers analytical skills crucial assets to achieving the desired competitive intelligence. Figure (19) summarises characteristics of marketing decision-maker, which are: value creator, communicating ability, IT knowledge, team player, analytical skills and clear articulation.

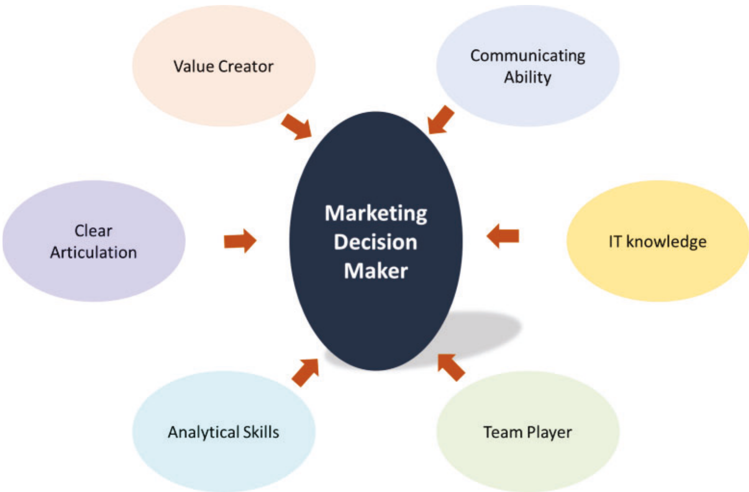

Figure 19 Marketing Decision-Maker characteristics

On the other hand, a change in top management, like a new CEO, reflects on the priorities of marketing plans. That is a substantial concern for marketing decision-makers because it changes consistency in directions and operations. Figure (20) presents the relationship structure and concerns between top management and marketing head.

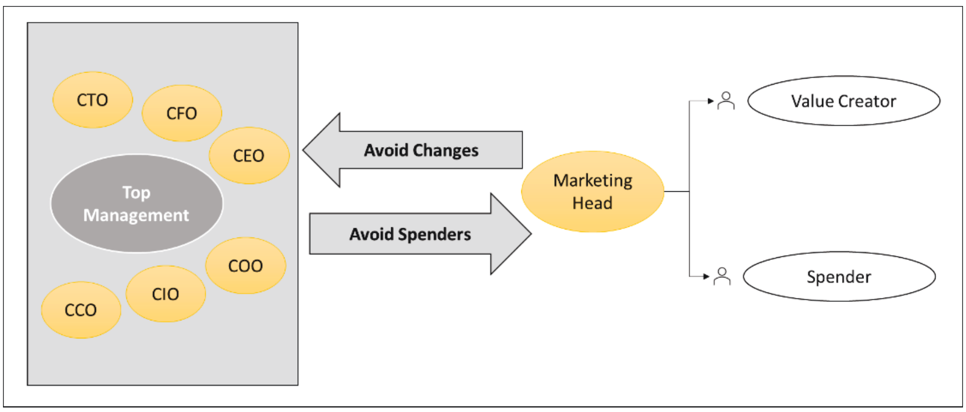

Figure 20 Relationship between Marketing decision-maker and top management

Practitioners have commonly used marketing head or marketing manager when referring to the marketing decision-maker. Responsibilities of this position are summarised below as has been described by practitioners:

1. Communication between top management and marketing department.
2. Preparing status report that contains current market statistics compared to the organisational goals.
3. Discussing, setting up and reflecting business directions with top management.
4. Defining and assigning marketing activities for the marketing department.
5. Activities timeline management.

Marketing decision-makers appear confident with the evidence-based intelligence that big data has created for them. Marketing decisions and directions are based on this intelligence. Two types of decisions are confirmed as per the findings: Long-termed decisions, referred to as Strategical, and short-termed decisions, referred to as Tactical. Some practitioners expressed that the short-term plans are embedded within the long-term ones, though they have more details and actions.

Strategical Decisions

As per the old saying: Before thinking of tools picking up fruits, looking at a tree, think of how to give water.

Working in a competitive real estate context have required practitioners to allocate organisational resources towards delivering particular messages to customers. Practitioners have discussed different topics underpinning strategical decisions, including positioning, brand equity, profitability, market share, and penetration.

The supply of real estate properties in the UAE is abundantly offered, giving customers plenty of options to evaluate before purchasing or renting. From this point, the research finds that creating emotional connections with the customer is essential for establishing a database of returning customers.

The findings also confirm that continual emotional messages are considered strategic for the organisation's competitive advantage. Despite that it takes time to embed behavioural changes, customers, throughout repetitive messages, will recall any related Ad or slogan that holds significance for certain needs.

One practitioner described the long-term messages campaigns as a tool to prove product validity and truthfulness by emphasising the organisation's competitive advantage.

Two out of five practitioners have come across the term price-elasticity as a benefit of well-defined strategical decisions. Over a long period, a returning customer becomes a believer in a company and would accept a price even if it becomes higher. The researcher observed that these practitioners work in the same large corporation known for its unique facility management.

Tactical Decisions

Practitioners referred to short-term plans, like monthly or quarterly plans, as tactical decisions. This type of decision entails providing and assigning the marketing activities to different channels and different marketing members who will be responsible for it.

The findings reveal that decision-making in the CI process goes first through strategical and then tactical plans. However, it was noticed that decision-making goes straight to tactical directions on some occasions (Figure 21). Environmental changes, which require Organisational Agility, force decision-makers to initiate "Ad-hoc" campaigns to change, adjust, and influence consumer behaviour immediately.

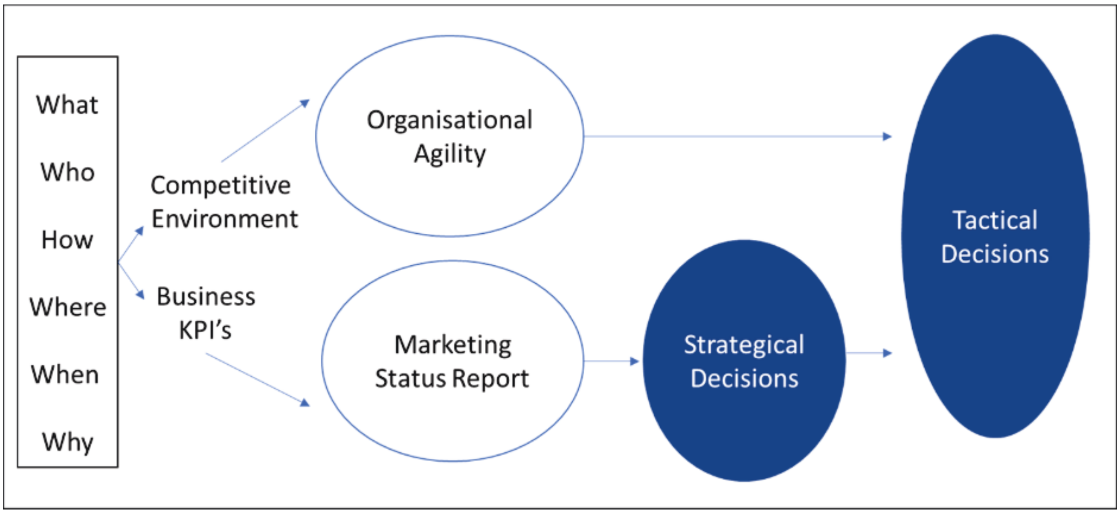

Figure 21 Tactical decisions inputs

All practitioners show a concrete belief in the necessity of taking risk if needed and jump to Ad hoc campaigns when required. "*You want to push brand competitiveness further; go outside the boundaries if needed!*" said practitioner G.

4.1.1.7 Decision-Making Process

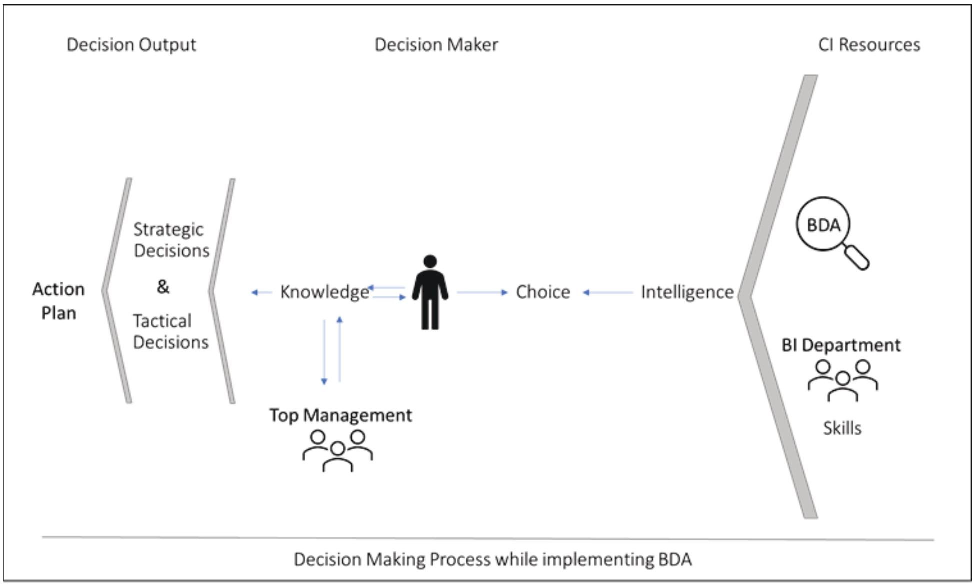

Figure 22 Decision Making Process while implementing BDA

Summarizing interview results of the Decision-making process: it was found that CI resource is the BDA, controlled by a skilled team from BI department. They provide reports of intelligence to the marketing decision-maker, who reviews and choose the required segments.

The knowledge created from the BDA is discussed with top management to ensure the directions of the campaign, and accordingly, two types of decisions are constituted: Strategical and Tactical. Based on findings, Figure (22) present the proposed Decision-Making Process structure while implementing BDA. Appendix E shows the proposed process compared to the conceptualised one based on literature review

4.1.1.8 Intelligence Dissemination

Competitive intelligence is desired to drive the organisation's mission and vision. Marketing goals have to be translated into actual actions and reflect the customer's experience successfully. Here, the decision-maker employs the produced intelligence reports to generate a marketing plan reflecting the strategical and tactical directions.

This phase seemed critical for practitioners because it is when the decision-maker distributes job responsibilities guided by meaningful insights.

Figure (23) presents the dissemination structure: Choosing the medium through which an audience encounters a marketing message, choosing the marketer/s who is/are in charge of the execution/s, providing a timeline for each activity, and clarifying deliverables and outcomes.

The findings reveal that the marketing mix is part of the continuous agenda for the marketing team during intelligence dissemination. Promotions and offers on property prices were dominant in the interview answers. One of the most important benefits of big data utilisation in the real estate sector is knowing how to target customers with the most attractive and suitable prices. Although practitioners emphasise promotions and offers differently (Appendix F), all of them agree on their importance while communicating with customers. Other (P's) of the marketing mix were discussed too: choosing particular locations to promote. Choosing the type of property to promote.

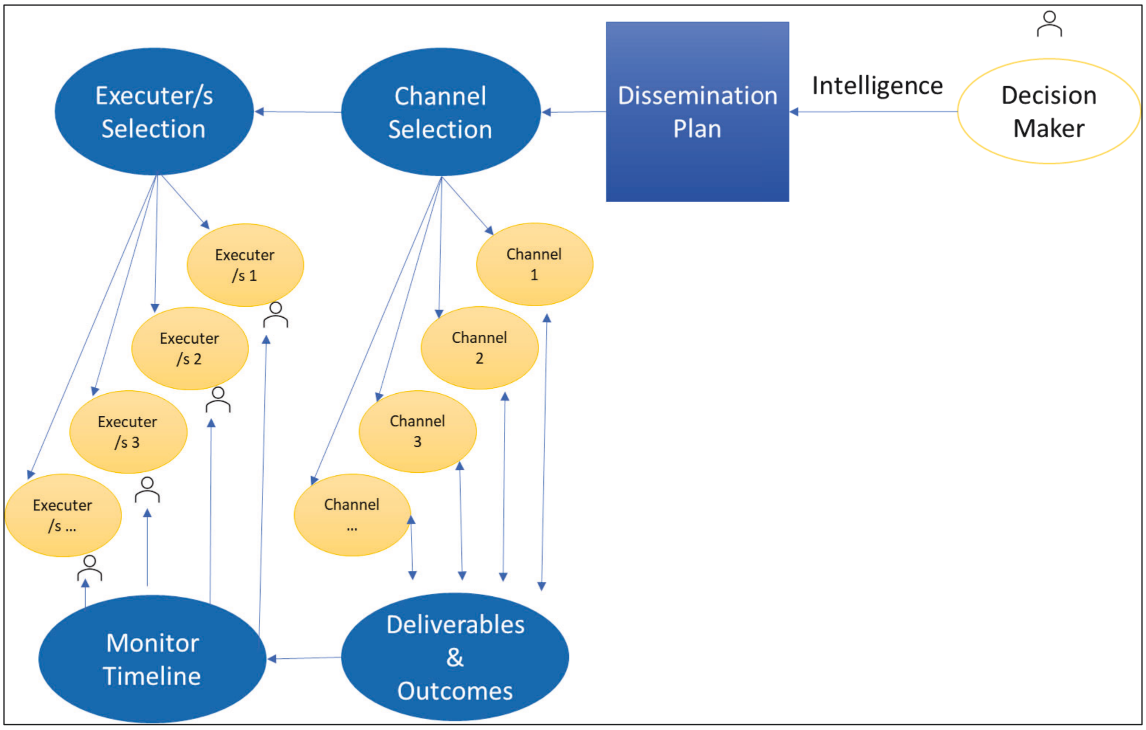

Figure 23 Intelligence dissemination structure

"During execution, I could pause a promotion in one channel and instead invest more in another promotion through another channel that brings us better results... If needed, I would stop or exclude using a particular user category that is not making money for us; for example, females aged 18-24 are not my user interest for buying properties because they simply do not have the purchasing power". Practitioner B

4.1.1.9 First Draft Model - Iteration 1

while consolidating all elements of CI process discussed by practitioners, Figure (24) presents iteration 1 artefacts of the first draft model, which draws upon the first-round interview results.

The new illustrated elements and the sequence of CI process will be assessed again by practitioner to confirm it efficiency to match the solution of the problem domain.

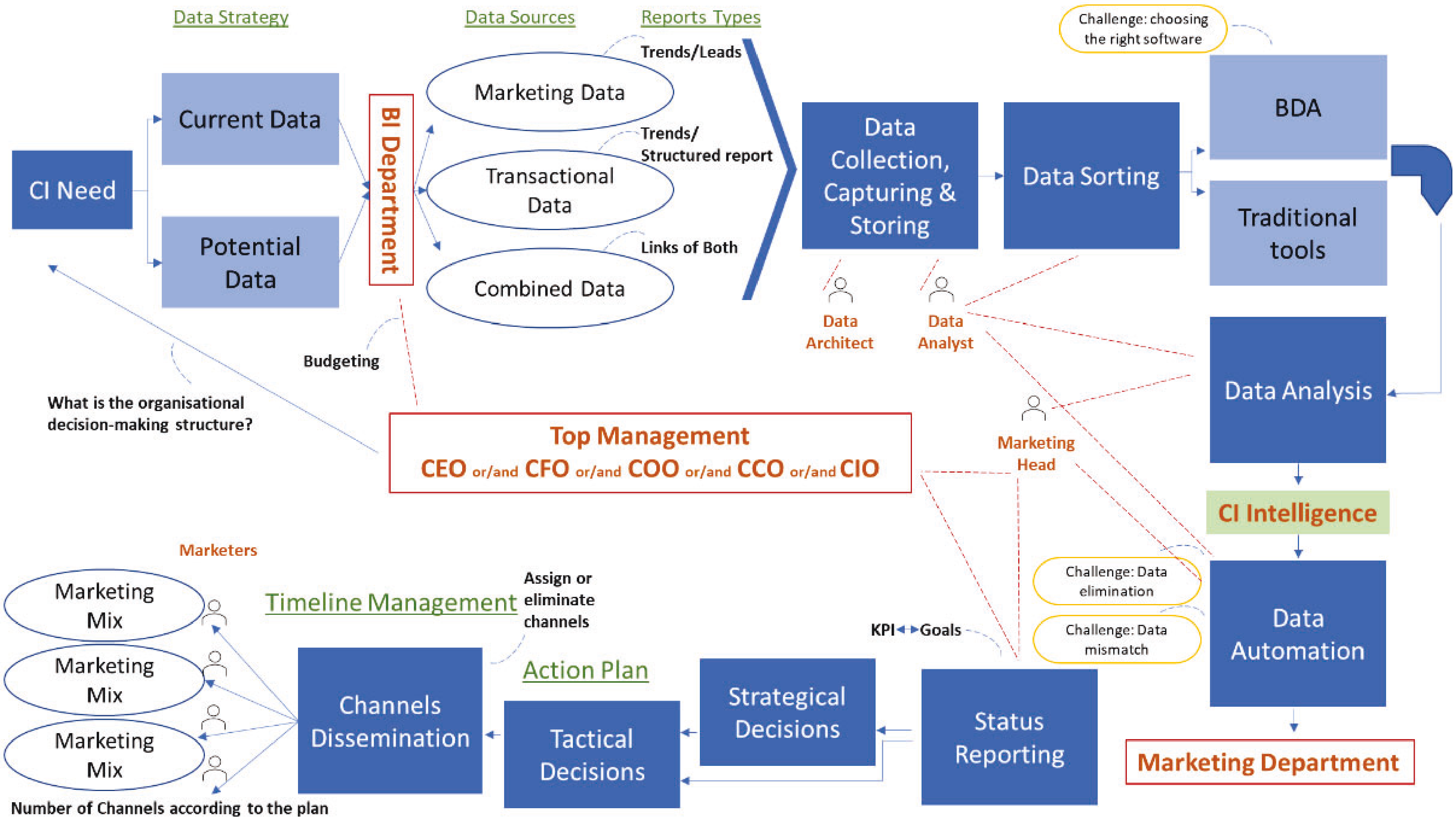

Figure 24 First Draft Model of CCIP-BDABM Post Iteration 1

4.1.2 Iteration 2

Interviews in iteration one has resulted in providing a foundation first draft model (Figure24) of the current organisational practices towards achieving CI while utilising BDA. The model constructs the flow of activities according to the existing corporate setting in a medium to large real estate context.

While evaluating artefacts produced in iteration 1, it was necessary to iterate interviews with the same practitioners to confirm CI elements produced. Participants appeared elated when they first viewed the first draft model. The graphical presentation, which demonstrates a description of their actual work setting, seemed of high interest to them.

Practitioners have all agreed that the CI process starts by identifying the *need* for using big data for competitive marketing purposes. Also, it was agreed that the identified CI *need* for the process is inspired and influenced by top management directions. At the same time, it refers to the vertical management style discussed and approved by practitioners about their current organisational approach.

This section discusses findings revealed from the second round of interviews with practitioners. Headings and sub-headings of this section are based on the interviews discussion.

4.1.2.1 Data Strategy

The first draft model shows that the Business Intelligence (BI) department practices data strategy. They first examine the current and potential data required for the CI project and accordingly proceed to data sources for data collection, capture and storage. All practitioners concur on BI responsibility for data strategy without any doubt.

Some practitioners commented on the report types produced by each data source. Their concern was that types produced from marketing sources are not limited to Trends and Leads as per the first draft model. Trends and leads, if solely mentioned, can limit the scope and capability of the marketing data source. Marketing data has various types, i.e., clicks, impressions, video, engagement rate, revenue, and conversions. These types are considered marketing's data KPI's that provide a benchmark of the market and the competitive environment.

The same applies to transactional data; some practitioners noticed that the naming of the data type is misleading. The first draft model listed two types of transactional data; Structured and Trends. Most practitioners discussed that if transactional data is is limited to structured data type, then the need for big data collection and capturing is diminished. Practitioners recognise transactional data as customer details generated by a transaction. Hence, there is always a chance that this data has a certain value missing, like timestamp details. Such missing values turn this data into being unstructured.

4.1.2.2 Big Data Analysis Phases

Data sorting, analysis and automation are all agreed in the correct allocation within the first draft model. There was consensus in the discussion that the analysis either uses or does not use big data analysis software. However, the majority reflected on applying the word *traditional*[5] as part of big data analysis. The concern is that the most commonly used software, i.e., Powe BI, demonstrates a traditional analytic tool within the big data context that becomes the best practice among corporate settings. Rather, and based on practitioners' explanation of possible circumstances of not using big data software, the researcher summarised this chance as *manual* data analytics instead of *traditional* data analytics.

Data analyst is responsible for data sorting as per the first draft model. However, in the second round of interviews, it is found that the data architect is argued to be involved in the data sorting phase, too, for the reason of being able to structure data setup and build the data warehouse.

Noticeably, practitioners have mostly discussed BDA through software recognitions, and accordingly, it was important to summarise the most highlighted and discussed software in real estate organisations (Figure 25). However, while comparing with results from academics' findings in iteration 1, academics have emphasised BDA discussion more about "venders" than "software". Therefore, it was important to

5 As discussed in the literature review page 60.

investigate with practitioners in iteration 2, on how they perceive big data vendors and why they did not come across and discuss any vendor in iteration 1.

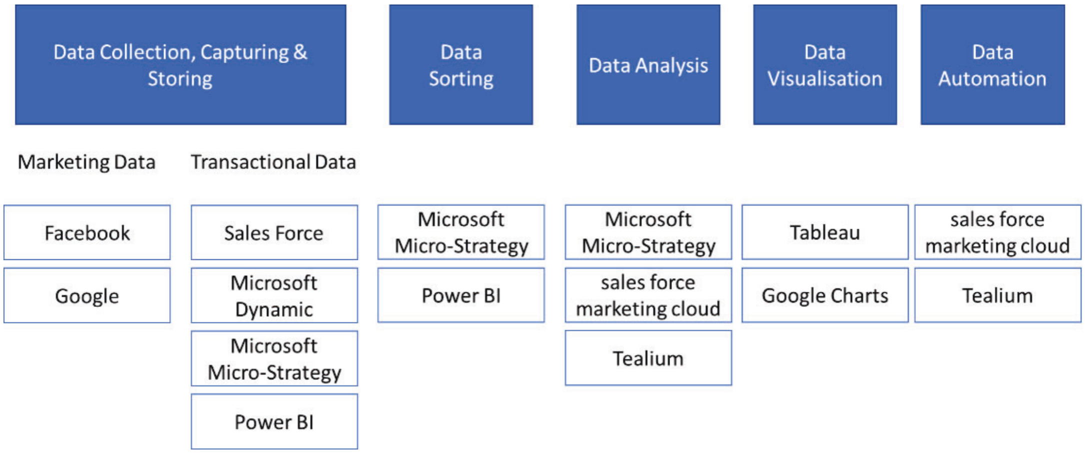

Figure 25 Commonly used big data software summary

Most practitioners acknowledged that if they have to choose a vendor, it will be SAP. Most practitioners described SAP as an effective vendor that can contribute towards CI, with a complete set of BDA phases. Some practitioners explained how SAP could build a website based on SAP language, and some discussed the effective marketing cloud, iCloud solutions and the CRM platform.

Oracle appeared next in practitioners' discussion, for the limited distinguished abilities surfacing in some phases of BDA rather than in all. According to practitioner C, Oracle can demonstrate phases of collecting, capturing and storing only. The research finds that medium to large-sized real estate organisations build their software and hire employees to implement it within the business structure. As per all practitioners, the reason for choosing in-house software is that vendors solutions are expensive.

4.1.2.3 Customer Data Platform (CDP)

The research finds that some organisations are likely to use CDP (Customer Data Platform) software. Practitioners claimed it to replace data visualisation tools in most cases during marketing operation day. Two practitioners discussed the company's utilisation of CDP and its importance for marketing campaigns and tools. Although CDP receives customers’ data from all marketing channels, it can normalise this data and create one profile for each customer, which is an added value for the marketing department. Some practitioners recognise CDP as a useful marketing tool that can speed up communications with each segment of current customers.

4.1.2.4 Big Data Analytics (BDA)

Practitioner C expressed that *"having received the desired analysis, I feel confident in my decisions".* The research finds that Big Data Analysis has provided marketing heads with the required knowledge for strategical and tactical decisions. According to some practitioners, intelligence based on BDA is claimed to offer market and competition knowledge, enabling marketing decision-makers to achieve a more effective competitive advantage.

4.1.2.5 Data Automation

Practitioners clarified data automation in iteration 2, repeatedly, similar to iteration 1. The benefits of data automation can benefit other departments like HR, Procurement and Finance. However, since the aim is to focus on the CI process within the marketing department, data automation in the first draft model is agreed to be the responsibility of both the marketing head and data analyst.

4.1.2.6 Marketing Reports

The first draft model shows the transition from BI to the marketing department. The marketing head takes over routine report generation from BDA solutions to an activity embedded in CI decision development.

All practitioners agreed on this level of transition as presented in the first draft model. One practitioner mentioned that status reporting could be named business reports; due to the unnecessity of receiving new BDA every time top management is met with.

Intelligence sense and numerical forecast figures are provided in status reporting to justify an action plan later. The vertical management structure is considered a logical hierarchy, where each individual possesses clear responsibilities. At the same time, some practitioners discussed a concern when top management is not present. In this case, they feel a time waste is likely to affect the CI. The decision-making will be delayed, and accordingly action plan is delayed too.

4.1.2.7 Segmentation

The findings reveal that BDA empowers businesses to customise marketing plans effectively, targeting the most suitable customer for each campaign. According to practitioner D, Customer Segmentation provides commercial values.

"*BDA provides the chance to move from one-fits-all to more customer-centric strategies*" said practitioner C.

According to the majority of practitioners, customers' segmentation is based on behavioural dimensions rather than demographics and value only. The behaviorally distinct groups are helpful for the business forecast and predictions like risk and revenue. They also help marketers execute better-targeted campaigns towards individuals rather than launching massive campaigns with a general message for all audiences.

One practitioner adds on BDA segmentation power for effective marketing decision-making, claiming that it is helpful to build a potential customer model when historical data is insufficient to do so. In this case, customers' segmentation based on BDA will support decision-makers to target customers from both current and potential databases.

4.1.2.8 Decision-Making

It was necessary to intend to discuss further ensuring the positioning of decision-making in the model. Therefore, practitioners were prompted to provide examples for the sequencing of tactical after strategic decisions and the possibility of skipping strategic and moving forward to tactical.

Answers were substantiated, and the flow of decision-making within the CI process is confirmed. The research finds that ad-hoc campaigns would jump to tactical decisions, skipping strategic decisions, due to the urgency of creating or adjusting new marketing content, or re-structuring channels distribution.

Practitioner B said: *"When X announced the Moh'd bin Rashid city launch seven days before what we expected, yes, we had to jump and adjust our digital appearance and offers and drag back customers' attention to what we have as well. Nobody would have expected me to set and decide strategically at that moment".*

4.1.2.9 The Marketing Mix

Iteration 1 has indicated that some of the marketing mix components may be more dominant than others. Price and promotion were mentioned most between practitioners in the first round of interviews; hence, it was necessary to investigate the marketing mix again in iteration two without hinting of a particular component that could lead to false influencing.

Results confirm that the marketing mix is utilised after dissemination. The 4 P's (McCarthy, 1968) are present in all discussions and confirmed that marketers in the real estate industry need to observe and monitor Price, Promotion, Product, and Place. The marketing mix of 4 P's are part of the internal reporting of the marketing department meetings. They contribute to other valuable discussions and evaluations on market trend, competitors, customer demand, behaviour, current budget, and extra budgeting. The researcher finds that the output of such marketing discussions can produce a formula for a successful competitive intelligence process.

Some practitioners came across the 7 P's unequivocally. Physical evidence, People and Process are found to be pre-determined separately to the CI process. Physical evidence is well established and maintained. The marketing department can comment on enhancing or branding related physical evidence wherever needed. People are professionally hired and monitored by the HR department.

In regard to the Process, the was noticed that practitioners recognise and discuss the CI process until the message is delivered to the customer. The sales funnel and closing of the purchase loop were not part of the marketing role and responsibilities. Findings reveal that sales and customer service departments are found to be responsible for contacting customers once approached.

Some concerns have been raised after the phase of monitoring the marketing mix. Most practitioners showed interest in updating marketing KPIs to be adaptive to the competitive environment of the real estate industry. Two practitioners mentioned that new KPI's could influence budget revisions, team re-structuring and marketing channels selections.

Based on practitioners' feedback on the marketing mix, the researcher summarised each component along with its CI usability in the real estate context:

Product: It is the property introduced to the market. Since there are varieties of property types, i.e., studio, one-bedroom, two-bedroom, apartment or villa, marketers choose the best type to use in the marketing campaign. CI based on BDA has helped in this decision, showing customers' demand and behaviour towards each type, and it has predicted the most desired type.

Product is what the customer is offered. In other words, Product is not limited to property type, it is provided with other factors that can enhance the company's competitive edge—for example, contracts, financial instalments, service charges, brokerage fees. Therefore, the product is composed of a bundle of factors that the customer appreciates.

Place: It refers to the actual location of the property and/or the selection of the channels to execute marketing campaigns and communicate with the customer. Both are considered to fit the Place term of the marketing mix. There is no particular property location that marketers focus on; it is changeable according to the intelligence reports received. On the other hand, social media, Google, and website are found the most efficient channels to communicate with customers.

Price: The value of the property has a large considerable impact on the marketing campaign's success, and it does affect the business strategy. The property Price presents the business positioning in the real estate market. This research found that the real estate industry, which is in favor of BDA, use the value-based pricing strategy. In other words, these organisations tend to understand customers' behaviour and expectations and accordingly choose to provide a property that matches what the customer expects.

Promotion: The real estate industry heavily manipulates promotional strategies to create a story for customers to communicate and increase product awareness and sales. Promotion is found to be the most dynamic tactic among the marketing mix in the real estate context. BDA allows the organisation to understand their customers and accordingly promote properties effectively using the right words and graphics.

The Nvivo analysis has proved that all practitioners have discussed Promotion the most compared to other P's of the marketing mix (Appendix G).

Physical evidence: Encompasses all existing experiences of the company, i.e., digital appearance, offices, building and communication channels, it seems that physical evidence is part of the business strategy. The findings indicate that physical evidence is not a tactical operation after data dissemination; all aspects are pre-determined and selected according to the current competitive environment. Hence, it is not an ardent topic for marketers on their regular meeting basis.

People: Refers to the sales and customer service departments who are in direct contact in selling, renting and solving customer inquiries. Findings reveal that the CI process does not touch upon areas concerning who actually talks to sell customers and how; marketers are focused on creating messages for each customer segment and delivering these to them successfully.

Process: Presents how customers move down the sales funnel. CI demonstrates tremendous potential to present the company's competitive edge up to the point of reaching the right customer. Despite that the selling process of communicating with customers can have the effect of either retaining and satisfying them or cause drop back and customer loss, however, it is found a responsibility of other departments, but not marketing.

4.1.2.10 Second Draft Model - Post Iteration 2

The study sought during iteration 2 to confirm on elements and determine the actual relationship between CI and BDA. Figure (26) demonstrates a holistic view, detailing artefacts of the CI process through BDA implementation extracted from results of second interviews findings.

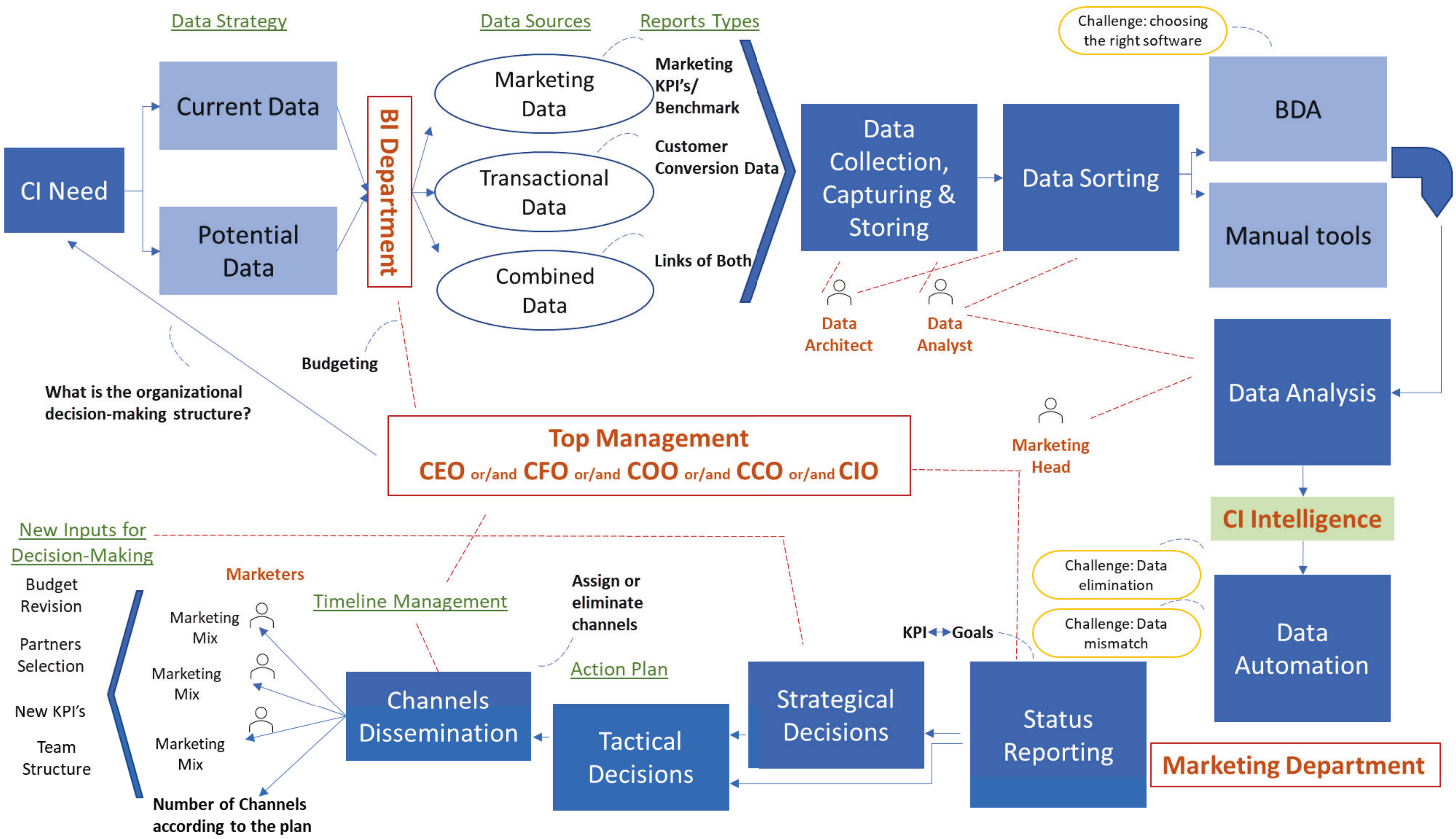

Figure 26 Second Draft Model of CCIP-BDABM

4.1.3 Iteration 3:

Iteration three interviews resume to confirm corrections of the second draft model. Practitioners appeared comfortable when listening to the CI activities steps narrated by the researcher. Next, they were asked whether they agree on the corrections or preferred adding or deleting any activity. They were all confirmative for the results achieved through the second draft model.

Status reporting remained the same and not changed to business reporting because most practitioners have consent for the name. The one practitioner who discussed business reporting has been questioned to confirm the naming of the marketing report, and accordingly, it has been agreed.

The degree to which changes were made to the process activities had relied on the knowledge flow towards forming competitive intelligence. It includes time management expected from each stakeholder and deliverables throughout the process. Building CI process of sequential reasoning is assessed against real-life activities in corporates-settings. Moreover, it is compatible with the current BDA utilisation.

This consent defines the objectives of a solution determined in chapter 1. The consensus represents an understanding of competitive business strategy, which can identify tools and methods to achieve competitive advantage. While aiming to achieve a logical conclusion, these corporate practices inform the conceptual solutions that will ultimately enable artefacts. Practitioners expressed their intention to use the resulting model, to use for competitive intelligence activities.

4.1.3.1 Final Model – Post Iteration 3

This feedback and the successful implementation of the method in practice enabled the study to manifest a novel CI process model that helps practitioners to follow a uniformed terminology towards achieving the organisation’s competitive advantage. Figure (27) presents the final draft of CCIP-BDABM based on findings results from practitioners.

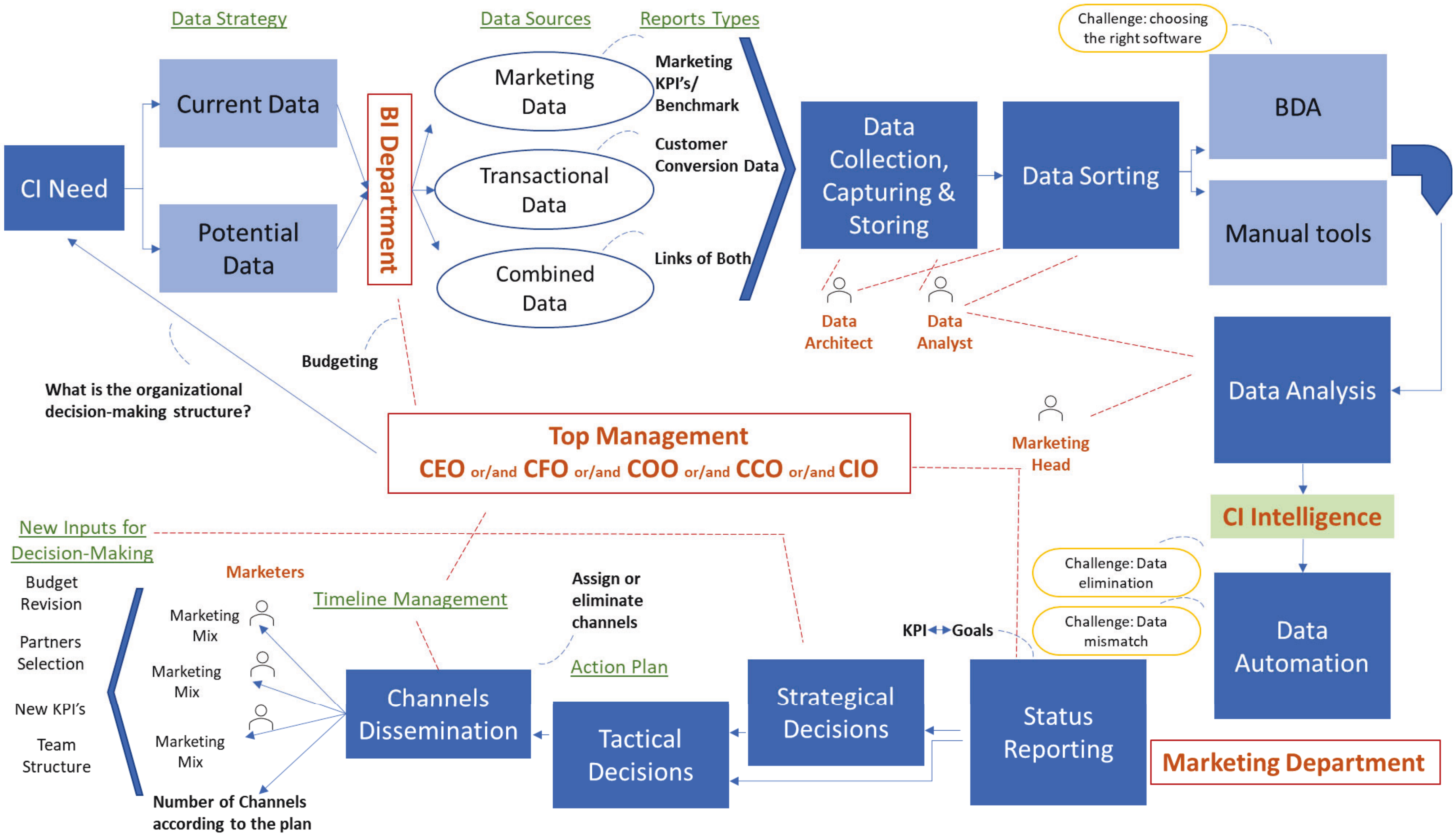

Figure 27 Final draft of CCIP-BDABM Post 3rd round of interviews with the experts

4.2 Findings from Academics' Feedback

Whilst the contributions from the practitioners' interviews were extensive and valuable in expanding and developing CCIP-BDABM, it remained the case that these results are informing and updating on practical corporate situations without touching upon updating on theoretical perspectives. As this is used to inform the context of the investigation, producing novel artefacts of the CI process, it was evident that the academic confirmation of the perspective would greatly influence the research material to recognise current differences or similarities between CI-BDA corporate practice and theoretical knowledge.

This is to confirm that it was a cognitive choice to interview academic experts of big data solutions, seeking to collect the current theoretical status of the subject. Iterative interviews applied the same, and this section provides academics' feedback on the proposed CCIP-BDABM (Figure 8).

4.2.1 Iteration 1

This section discusses academics' initial feedback on the proposed CCIP-BDABM, which demonstrates phases of intelligence creation until delivering messages of competitive advantage to the target customers. The headings under this section were informed by the discussions that took place throughout the interviews.

4.2.1.1 Planning

It was found out that that *CI planning* is a valid term for academics. All academics responded to the question (is *planning* the first phase of the CI process?) with non-hesitated acceptance. The explanation varies slightly in terms of how planning is implemented. Academic A and C discussed the necessity of scanning and evaluating the environment, studying all internal and external variables related to the market. Understanding the competitive environment is a vital phase required before planning for CI; academics claim it speeds up the preparation and execution for competitive intelligence.

Academic B discussed that planning is based on competitors and what the competition implies for the business to do. More emphasis was on the perspective of surviving dynamic competition and any rapid changes in competitors' products and offers.

Also, part of the discussion were competitors' strengths and weaknesses, particularly competitors' communication speed with customers. Academics entail the importance of having well-trained sales and customer service departments who can respond quickly and with full efficiency.

Overall, and since competition is a concerning part of the competitive environment components, it is concluded that it is important to scan the environment before planning for CI. This environment signifies all information that is useful to create a competitive advantage and enable decision-making to sustain a strong competitive presence.

4.2.1.2 Data Collection

Two themes emerged from data collection: data creation and data capturing. Both terms relate to the same data collecting activity, but they emphasise creating a new database with new dimensions or gathering data distributed between departments and not yet normalised in one database pool.

Some academics felt that campaign dimensions restrict data collection. This occurs when dimensions are regularly changed, causing confusion for data analysts as well as wasting time and effort. Also, one academic considers data availability and accessibility to control the data collection activity.

These views surfaced mainly in terms of how data collection starts. In other words, two divergent and often conflicting discourses emerged to reflect how strategy shapes the data process. The big data strategy in the CI process either starts upon what has to be collected to fit the marketing goals or upon what database is available.

It is found that data sources vary between social media, e-commerce platforms, enterprise portals, sensors, CRM systems, Enterprise Resource Planning (ERP) systems and Supply Chain Management (SCM) systems and all sorts of systems at the level of enterprise. Academics agree on the Business Intelligence (BI) department that captures data and integrates it into a pool of databases that can be utilised for data analysis and meaningful insights.

Academic A emphasised data sources being distributed between all departments. The data is collected and integrated from different departments: "*Product data comes from the supply chain or warehouse, the costs -for example a hundred dirhams- are from the finance or sales department, key selling points data from the marketing department, and the targeted customers are from marketing or the customer service department*".

4.2.1.3 Data Processing and Storing

Interview results suggest that there is an association between filtering and sorting; these activities are identified as data processing. Participating academics recognise any sort of data preparation and normalisation, including filtering and sorting, as one concrete step towards storing data that is ready to be analysed.

A minority mentioned that filtering the data can proceed directly to data analysis; all agreed that data storing will take place after data processing. Normalised data goes to a data warehouse, which supplies data analysts with the required data to analyse, however, some data might not necessary be found at this time and will go to the data archive.

The majority stressed the importance of the data warehouse, which stores multidimensional current and historical data. As academic C put it, historical data of more than ten years can greatly impact current decision-making. The statement implies the importance of archived historical data, primarily when provided with patterns that can explain consumer behaviour.

Academics suggest no one software; rather, it is many options offered in the market. All academics insist on the organisation's necessity to define the desired big data outcome before the software selection. The researcher was able to summarise academics' concerns about investing in big data software: Budget of big data investment, employee skills availability and capability, objectives of big data project and the expected deliverables. Figure (28) presents academics' feedback on challenges of software selection.

Academics report that key player vendors of big data are notable in each region. Around the Gulf region, two academics said that the best player in the region is

Oracle6. On the other hand, one academic mentioned that Oracle was the best player in the Gulf, especially for the HR module; however, now the migration is to SAP7.

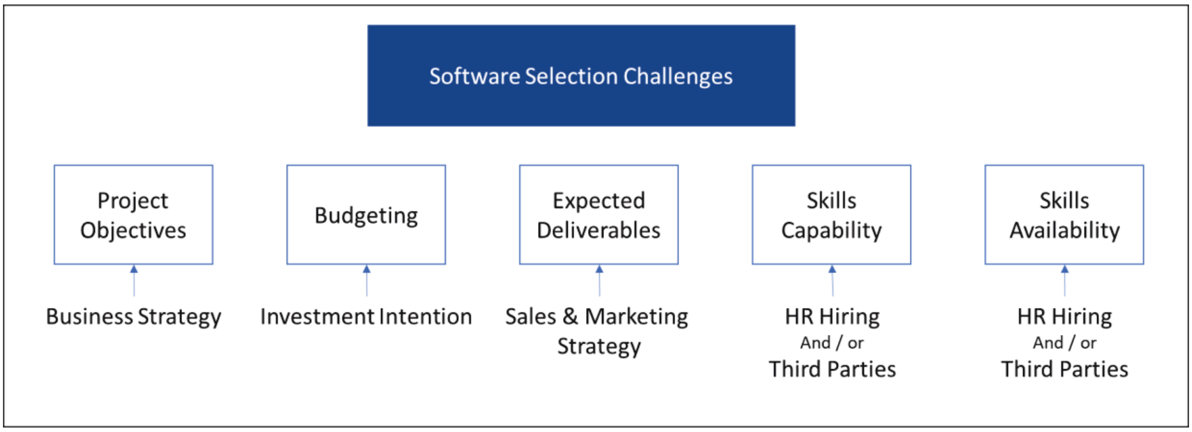

Figure 28 Challenges of software selection as per academics' feedback

The findings from academics' interview results reveal that critical marketing decisions surrounding competitive environments such as competitors, consumers, sales patterns, and best practices that are old or new can be derived from big data and provide actionable intelligence to enhance the competitive edge for the organisation.

4.2.1.4 Data Analysis

All academics believed that the data, with completed processing and storing, is ready for analysis. Academics abundantly discussed issues on how data is analysed. Data mining is a major topic within the data analysis step; it provides the importance of sequencing data with a time series, finding what is common between categories among different sources, especially if the organisational direction is based on multi-dimensional data.

Data forecasting, association, prediction and sequencing are summarised as data mining capabilities, which can be provided by BDA. It presents the ability of big data to enforce decision-making.

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6 ORACLE is a comprehensive and fully integrated cloud applications and infrastructure. Source (www.Orcale.com)

7 SAP is one of the world's producers of software for the management of business processes, developing solutions that facilitate effective data processing and information flow across organisations. Source (www.SAP.com)

Data forecasting, association, prediction and sequencing are summarised as data mining capabilities, which can be provided by BDA. It presents the ability of big data to enforce decision-making. Two academics discussed the correlation analysis of big data, and the expectation of the outcome of either certain or uncertain.

Findings from academics' interviews expressed the necessity of decision-making activity after BDA insights are received.

The intelligence should be tested for the level of certainty, which accordingly a decision-maker agrees as to whether or not to take action concerning. Concerning certainty level, two academics discussed the importance of big data correlation analysis and the expectation of either certain or uncertain outcome.

Most academics argue on the higher possibility of returning insights to a level of analysis where it is investigated further to achieve a higher level of certainty. Academic A believes that most modern businesses are taking the risk of accepting uncertain insights and putting them at risk of action trial. Appendix G is a screenshot of Nvivo analysis showing what academic A has expressed about uncertainty analytics.

Academics come across the OLAP8 system, however academic A has discussed it more extensively. During the interview, it appeared that academic A had done research on data analysis and personally used and demonstrated the OLAP system. The importance of OLAP - On-Line Analytical Processing - has risen due to providing real-time intelligence to the data analyst, using multi-dimensional data.

Academic B discussed the role of the business analyst and system analyst too. Besides the vital need to differentiate between these roles and the data analyst role, academic B mentioned that business analysts are the decision-makers who receive the big data insights from data analysts, turning it into business solutions.

"The most important is how to interpret, and read the hidden answers, and discover the facts behind it" Academic B said.

8 OLAP is a technology for data discovery, including report viewing, complex analytical calculations, and predictive scenario (budget, forecast) planning. Source (www.Olap.com)

4.2.1.5 Decision-Making

The CI decision-making structure appeared well defined according to academics. The process of carrying vision into implementation is organised through sequential steps. Academics' answers concerning the strategical decision level are similar; it holds the business vision and values, being the responsibility of senior management represented with the C-suite of Chief Executives. This level contains different organisational aspects covering all departments of the organisation.

The related marketing aspects proceed from the Chief Marketing Officer (CMO) to the marketing manager, translating vision into a mission. Academics recognise this phase of decision level as tactics or tactical decisions. Another level of decision is operational; it is when these tactics are implemented operationally by the marketers. Figure (29) presents the decision-making structure based on academics' interview results.

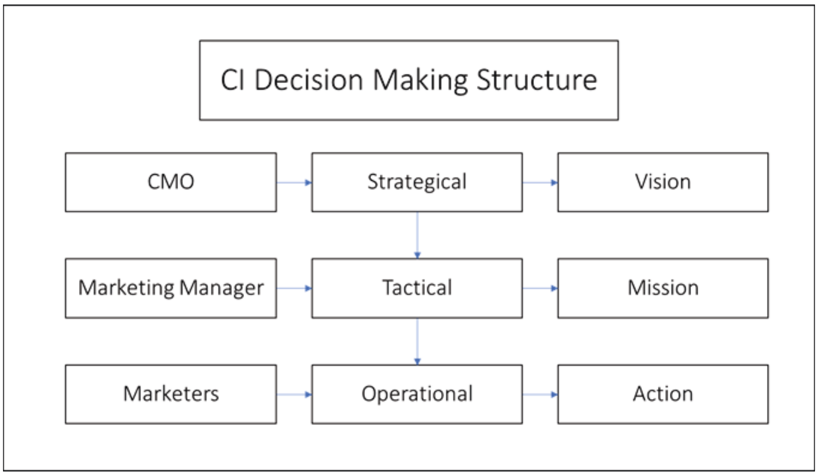

Figure 29 CI decision-making structure based on academics' feedback

One academic believes that big corporations are most likely to have a bureaucratic managerial structure, which causes long information flow and, consequently, fewer innovative ideas being implemented.

4.2.1.6 First Draft Model - Iteration 1

According to feedback from academics during iteration 1 interviews, the first draft model was constructed presented in Figure (30).

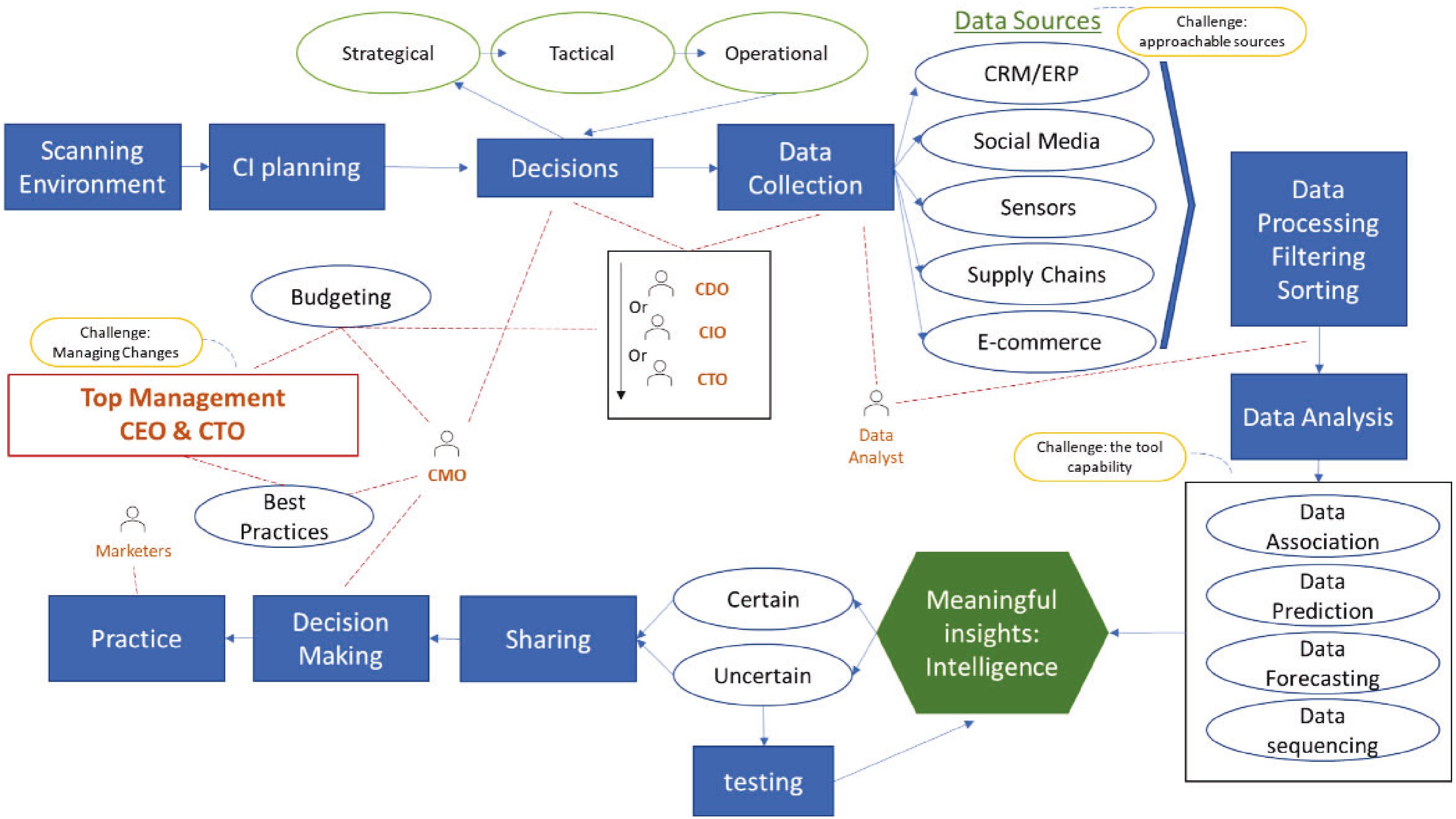

Figure 30 First draft model based on academics' feedback

4.2.2 Iteration 2

Demonstration of proposed CCIP-BDABM during iteration 1 interviews with academics have confirmed necessary elements and process sequence of competitive intelligence while adopting BDA technology. However, it was necessary to evaluate the results and iterate interviews throughout a second round to confirm artefacts. Feedback collected from iteration 2 has coincided with most of the cycles within the first draft model (based on academics' feedback). Some results and discussion had been raised from the second-round interviews listed as per the topics below.

4.2.2.1 Decision-Making

Academics' answers appeared consolidated and unified in terms of process activities and sub-activities. They perceive the flat management structure as appropriate for the organisational CI process. Teams and employees are provided with autonomy to produce competitive intelligence according to the business goals and objectives. It is found that decision-making activity takes place twice in the CI process: First is before starting the data collection, and second is before marketers start the campaign.

it is important to highlight how the academics perceive levels of decision making. Each level has certain positions to provide directions for it. Table (4) summarises levels of decision-making and delegates of each level as explained by academics.

Table 4 Decision-Making levels and delegates of each level based on academics' feedback

Strategic Decisions	Tactical Decisions	Operational Decisions
CEO, CFO, CTO, CIO, COO, CMO	Marketing Manager IT Manager	Marketers Developers

4.2.2.2 Scanning the Environment

Discussion with academics revealed that environmental scanning should be detailed, unlike the first draft model based on academics' feedback, to present internal and external factors. Stressed by some academics, the internal resources are the tangible and intangible resources. External resources are summarised by opportunities and threats based on the SWOT analysis report. This information is valuable to plan for better or new solutions and opportunities. Academics agree that exploiting internal capabilities and external resources can help meet the demanding standards of real estate competition and provide a competitive advantage for the business.

4.2.2.3 Best Practice Cycle

The research finds that best practice is necessary to be mentioned in the model. It is produced from multiple practices until reaching the best among them. One academic emphasised this cycle for the benefit it provides to marketers in particular. The action plan presented by the practice is an iterative cycle that functions as much as required until it reaches the best practice. It starts with implementation, then feedback and improvement. Accordingly, the best practice cycle is found necessary to be added within the last phase of the CI process.

4.2.2.4 Second Draft Model - Iteration 2

Figure (31) presents the second draft model based on academic' feedback in iteration 2 interviews.

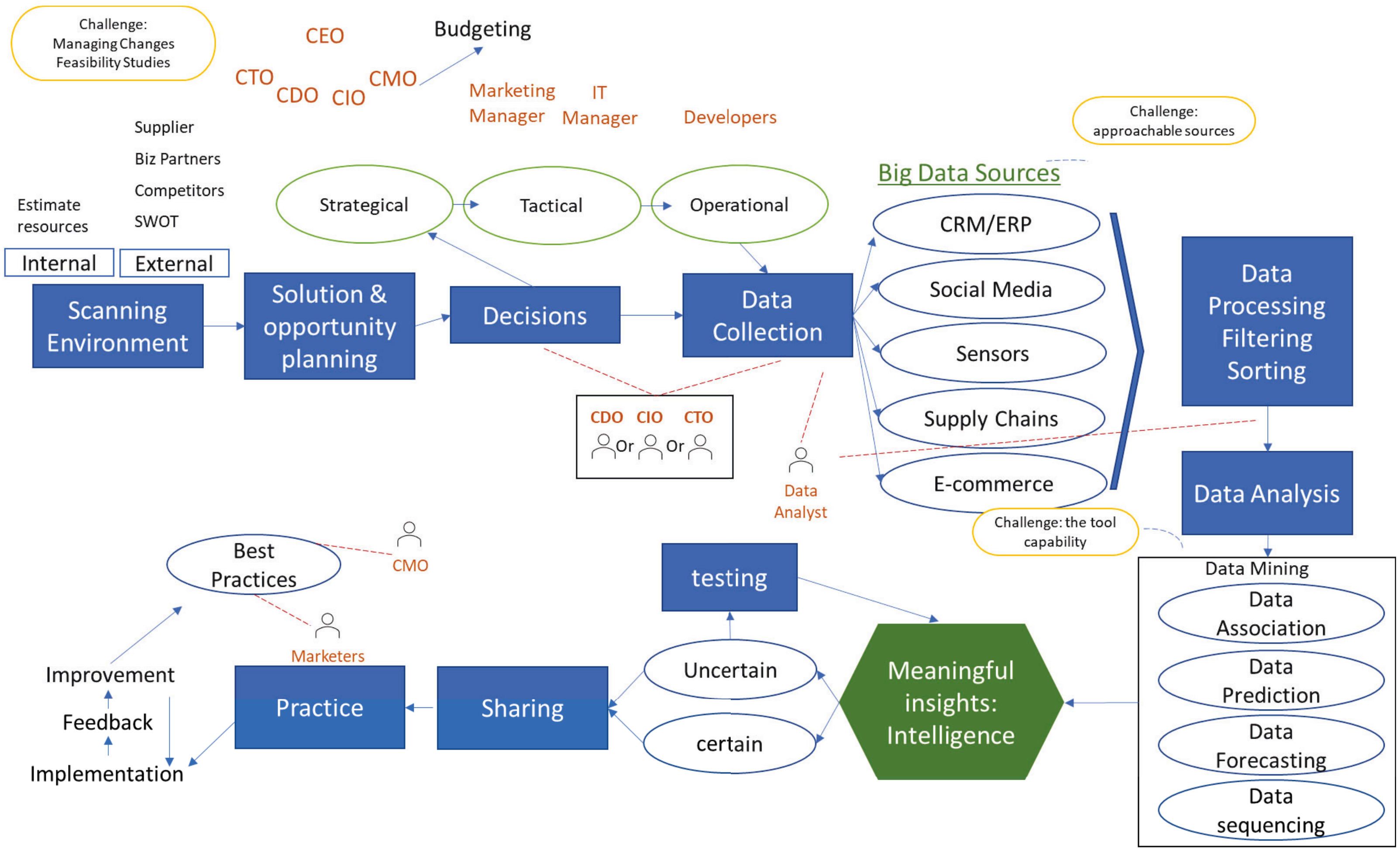

Figure 31 Second Draft Model based on academics' feedback

4.2.3 Iteration 3

All academics appeared cautious on the sequential activity orders. Therefore, the CI process was narrated slowly (by the researcher) to cover all CI components. Academics believe in digital transformation initiatives, including BDA, because it enables organisations to become more agile and customer focused. Academic A expressed the integrated BD solutions is likely the backbone of competitive marketing initiatives.

Few points were part of the discussion, with a minor correction. Two academics discussed the naming of *certainty* and *uncertainty* terms of intelligence reports. Academic A said that, in a business setup, a low level of uncertainty should not hold or delay operations to proceed further. Also, *Data clustering* was added as one of the data mining activities. Moreover, *sensors* were discussed by all academics to be reviewed under another term which is the Internet of Things (IoT) referring to all interrelated computing devices.

Academic C stressed on the timely mannered customer's segmentation empowered by BDA being helpful for the marketing decision-maker to deliver more successful campaigns that deliver organisations' competitive advantage.

Academics support the view that the intelligence possessed by BDA implementation is among the most remarkable of an organisational capability and may ultimately be at the root of achieving business competitive advantage. Their discussion of the technological capabilities matches with practitioners' interview results pointing of BDA as Capability-Based View (CBV) to support the competitive advantage.

4.2.3.1 Third Draft Model – Iteration 3

Based on corrections received from academics upon second draft model, a third draft model of academics' feedback is proposed bellow (Figure 32).

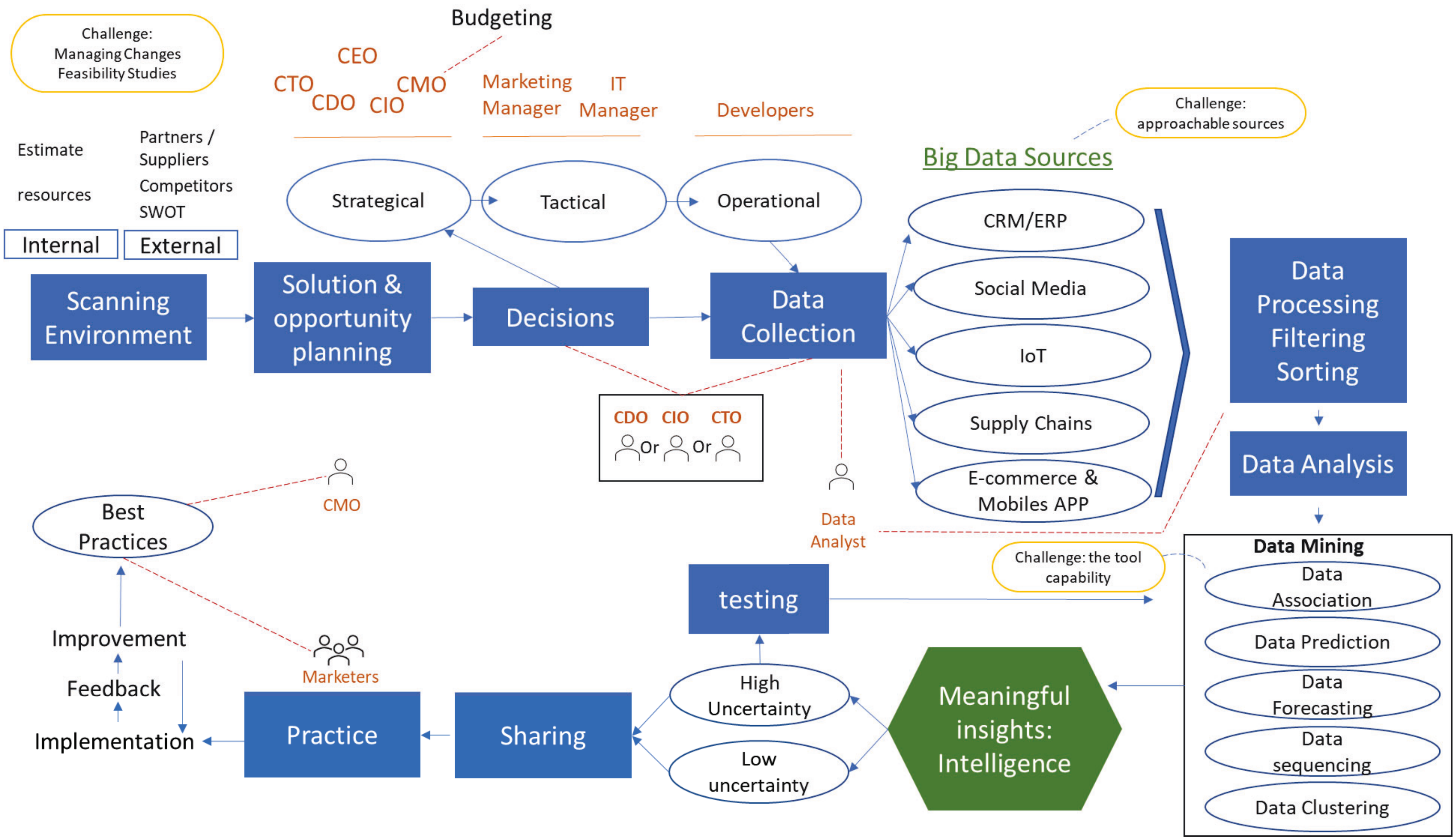

Figure 32 Third Draft Model based on academics' feedback

4.2.4 Iteration 4

Academics in iteration 3 were cautious on the process sequencing and the terminology used for it. Few corrections of naming some terms and some additions to data mining and best practice cycle were all added to the third draft model. Accordingly, it was necessary to evaluate the addition of these elements and confirm their role in the process.

The fourth round of interviews with academics took place to confirm the resulting artefacts. All academics have agreed on the Third Draft Model (based on academic' feedback), and therefore there was not further changes to the model presented in Figure (32).

4.3 Gap Analysis between findings from practitioners and findings from academics.

The DSR demonstration activity was to construct and gain knowledge from practitioners and academics to develop solutions to the research problems in the world of practice and thereby generate insights for the world of theory.

Insights from discussions from both practitioners and academics have led to highlighting some differences between the two parties. The mismatch viewpoints that appeared are not at the core of CI process; it is a derivative perspective of perceiving the project. However, there was a need for a comparison between the two inputs.

Following validated business practices that apply fit and gap analysis (Dejan and Andrej, 2013) can improve the organisation's agility to represent a strategic competitive advantage. A comparison between the two models is conducted to benefit practice and theory, and thus this section focuses on a thorough comparison between the two perspectives. A set number of criteria are found and discussed below:

1. The sequence of CI process and activities from start to end.

2. The characteristic of decision-making structure and naming of decision-maker.

3. The degree of top management influence on CI activities throughout the cycles.

4. BD technological recognition.

5. the dissemination phase

4.3.1 The CI process sequencing

Practitioners believed of identifying CI *need* as an entry point for the process, while academics agreed on the necessity of *scanning the environment* before *planning* for CI. It seems that practitioners beieleved they understood the environment, including internal and external factors, assuming BI department have provided related reports using BDA. Thus, they started into a direct investigation of the purpose and *need* of CI. worth mentioning, Saayman’s et al. (2008) model matches practitioners feedback of CI entry point.

On the other hand, academics have agreed on keeping CI planning, similar to Pellissier and Nenzhelele’s (2013) model; however, they assumed another activity should take place before, which is scanning the competitive environment. Figure (33) illustrates the difference between both results concerning the first activity of the CI process.

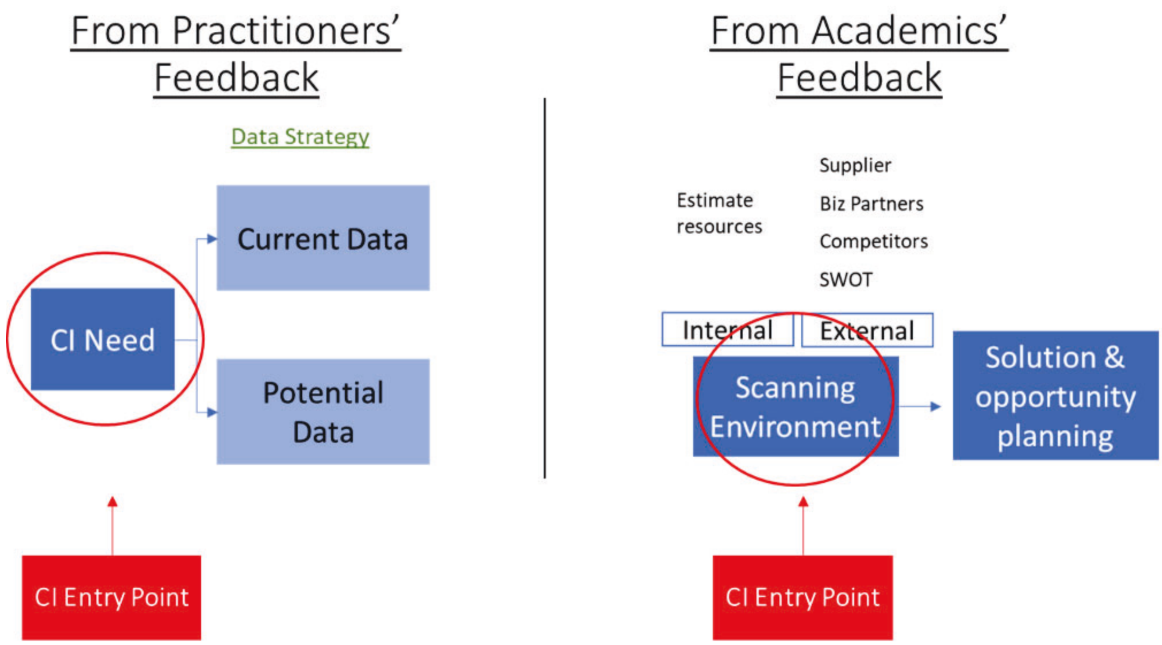

Figure 33 Difference of CI entry point between results from practitioners and academics

4.3.2 The characteristic of decision-making structure and naming of decision-maker.

Two points are found different between the two findings:

- Management decision structure

Notably, the management structure seemed a big difference between the two findings. Practitioners described the management structure as vertical, while academics described it as horizontal.

While the vertical management structure implies two decision levels, the horizontal structure comprises three decision levels. In one interview with an academic, the results showed a concern of time wasted caused by three layers of decisions. Comparing this academic concern to the corporate field, it seems that decisions in practice have come through this concern and jumped into shortening the decision levels into two only.

- CI decision-making

The decision making, as an activity of CI, appeared located differently in each finding. Practitioners demonstrate related actions of decisions after the intelligence being produced. On the other hand, academics see the decisions are allocated at the beginning of CI planning.

Regarding the marketing decision-maker, the Marketing Head is considered the primary decision-maker of the CI entire process, based on practitioners' findings. Academics have considered the Chief Marketing Officer (CMO) as the primary decision-maker in the marketing department.

4.3.3 The degree of top management's influence

Top management support of approving and facilitating CI process is an essential component of the Organisational Agility. Both practitioners and academics had not doubted of the above statement.

However, practitioners explained the necessity of communication with top management in multiple areas throughout CI process; Budgeting at the beginning of the process, support IT infrastructure at the middle of the process, and time management observation between channels dissemination and achieving deliverables. On the other hand, and as per results from academics' interviews, top management support appeared only at the beginning of the process.

4.3.4 BD technological recognition

It was clear that results from practitioners are dominated by discussing the software and the technological integration toward achieving CI. For example, some names of software were repeatedly discussed, like Power BI. On the other hand, academics had mostly expressed vendors significance of technological intervention and impact on the competitive advantage. The most discussed vendors were SAP and Oracle. During interviews discussion, findings have highlighted that some practitioners did appreciate vendor's system solutions; however, the disadvantage as per practitioners was:

1. Expensive cost
2. Long term tie-up with vendors appears to have had third parties less interested in the project.

4.3.5 Dissemination phase

Concerning dissemination activity, academics have continuously referred to the term Best Practice as the optimal objective of this activity. The practice, as compared to practitioners, is the actual work that marketers execute according to the marketing plan. Instead of referring to best practice, practitioners discussed their expectations of errors raised during execution, emphasizing on having a backup plan to eliminate current activity or apply additional analytics to re-test the outcomes.

4.4 Critical Discussion

Based on the results concluded in the Findings, some topics are found necessary to be critically discussed.

4.4.1 Competitive Environment and Organisational Agility

Compared to business challenges before big data, the heterogeneities in environmental changes (Allison et al., 2020; Miller and Friesen, 1983) are challenging organisational strategies and can cause an internal structural glitch. Marketers must collect real-time market data to be analysed instantly (Henschen, 2013), allowing decision-makers to adapt to a new direction for environmental changes. The literature review discussed environmental changes; for example, new competitors providing substitutes (Sharp, 2009) can change consumer behaviour unpredictably. Therefore, the literature suggests seeking effective market intelligence analysis strategies utilising external market resources (Ullah, 2021) to collect the new purchase patterns that influence customers.

Based on this study's findings, Organisational Agility appears dominant within current business strategies; it helped decision-makers perform notable competitive strategies of favourable competitive edge, and also it allowed to adapt with the market and environmental changes (Nwankpa and Datta, 2017). Moreover, the speed of environmental changes (Kumar et al., 2020; Gupta et al., 2018) and the speed of analysing environmental data (Gupta et al., 2018) are embodied in big data and BDA. Thus, this research confirms that big data technology is a valuable component of Organisational Agility; it has sense and response abilities (Overby et al., 2006) that can detect activities and changes in the business environment. Also, because knowledge and internal mechanisms lead to Organisational Agility (Liu et al., 2010; Mao et al., 2015; Allison, 2021), this study has confirmed that big data can provide descriptive, prescriptive, and predictive analytics, which are a meaningful input to the organisational knowledge (Serra et al., 2018) while operating through software which demonstrates the internal mechanism.

On other hand, this study argues that top management support is an adequate internal mechanism towards achieving the desired business performance. The finding confirms that BDA adoption, clear business direction, and time management monitoring are all three critical factors that require top management support. This support is an essential asset of internal mechanism that contributes to the successful organisational agility

4.4.2 Decision-Making

As per the research findings, decision-makers are confident with the evidence-based (Connelly et al., 2014; Allison, 2021) intelligence extracted from big data. This confirms the claim by Adrian (2017) that decision-makers seek pertinent information with a reduced probability and uncertainty. This study’s findings confirm that capitalising in big data technology can perform as an internal business resource (Ullah, 2021; Wernerfelt, 1984; Linden and Teece, 2018) that can understand external resources and accordingly provide prediction analysis to decision-makers. BDA has performed in this study as a core competency for marketing decision-making, using technology endowment (Tidd and Tidd, 2006) to collect market insights.

Also, the multi-intelligence theory by Garners (1990) suggested elective cognitive selection to harness desired performance. Among the eight types which Garner proposed to increase the effectiveness of decision-making, few types only matched with this research findings. First, the *interpersonal* skills demonstrate the capacity to understand the intentions, motivations, and desires of other people (top management) and, consequently, work effectively with others as teamwork, communicating what you need from them (data dissemination). Second is the intrapersonal intelligence is required when making decisions; transcribing top management’s directions and the current achieved knowledge towards prioritising what’s important and how to achieve it. The third is linguistic, which is the capacity to use language to accomplish certain goals (give directions). Naturalist intelligence is applied for the context awareness of the competitive market and its components.

The bodily-kinesthetic intelligence, of using one's own body to create, perform or solve skills and problems, is not needed and the same is applied for musical intelligence. The remaining intelligence in Garner's theory is embedded through big data solutions;

The logical-mathematical and spatial skills appeared demonstrated by BDA, provided through the ability to recognise and manipulate large-scale and fine-grained spatial images, in addition to the ability of developing equations and proofs. In other words, finding confirm that Decision-makers are no longer required to demonstrate all skills; BDA took over some skills already.

Academics have recognised and defined the marketing decision-making process similar to discussing Simon's model (Simon, 1977), emphasising procedural rationality rather than substantive rationality. Simon's model appeared valid for practitioners' discussion of decision-making too. Simon identifies decision-making based on environmental characteristics that first provide problem identification and select alternatives of choices based on the problem. Among the identified CI needs for decision-makers, one choice of a need will be selected for which a process of analytics will continue to provide the intelligence. The research confirms that current CI decision-making follows the procedural rationality of Simon’s theory, through choice and alternatives.

Both practitioners and academics have discussed the decision-making factor abundantly. The naming of decision-maker slightly varied between them. For practitioners, the marketing decision-maker is commonly called a marketing head or marketing manager. This finding matches with what Chen (1995) claimed that marketing managers are the core of CI and hence they are the decision-makers. On the other hand, academics have named the marketing decision-maker Chief Marketing Officer. The finding appears similar but not identical to Tawodzera’s (2018) who claimed that the CI decision-maker is the director, followed by manager and staff.

The literature review discussed the fact that extracting meaningful insights is a major obstacle for effective decision-making (Pellissier and Kruger 2011), that being basically due to lack of skills and knowledge (Fleisher and Craig, 2004), as well as for the challenge of reading contradicting information (Kumar et al., 2020). Moreover, the concept of similar circumstances information by Ian Norris et al. (2020), which is claimed to provide inadequate knowledge causing less experience and intuition, leads to the concern of meaningful insights extraction.

In fact, this research findings confirm that organisations receive a huge amount of behavioural and transactional data, which helps marketing decision-makers target each customer based on their segment group. In other words, current software utilised by organisations empowers decision-makers with the desired meaningful insights that they can take forward for marketing plans and executions. The main challenge though regarding the meaningful insights is that the BI department must ensure solving any error and heterogeneity occurred from big data which mostly reported to be acquired from fake inputs from data origin.

The findings also demonstrate the difference between nowadays decision-making challenges while utilising big data technology (Russom, 2011; Serra et al, 2018; Sun et al., 2020) and other organisations that still use traditional tools and techniques (Aljumah et al., 2021). Practitioners were comfortable with software abilities like data mining which can do associations and predictions between different data sources, demographics, and environments. Also, utilising the Customer Data Platform has provided decision-makers with knowledge (Ghasemaghaei et al., 2017) and the ability to respond with precautions (Slaouti, 2021) while supporting business performance.

The difference in the gap analysis related to the decision-making structure of vertical and horizontal, two levels or three levels of decisions, can be justified by the necessity of corporate setting to reset the decision-making structure claimed by Christine (2021). The finding confirms that current organisations apply a dynamic process of decision-making to survive within the competitive market. In fact, the findings revealed that academics showed concern about time waste based on the horizontal management structure. This also confirms the importance of dynamic capabilities in terms of decision making.

4.4.3 Dissemination

While checking back on the literature review, CI models have had dissemination as a last cycle of CI (Sawka and Hohhof, 2008; Madureira et al., 2021; Kahaner, 1996; Bose, 2008; SCIP, 2007; Yin, 2018; Fleisher, 2008; Pellissier and Nenzhelele, 2013; Saayman et al., 2008; van den Berg et al., 2020). In mind of the organisational culture and competitive environment, this last activity monitors the feedback and recommendations (Bose, 2008; SCIP, 2007; van den Berg et al., 2020).

The research findings argue that another phase is required to add within CI process elements while implementing BDA. Summarising practitioners' and academics' feedback, approaching best practices through a flexible deployment of the marketing mix is required. There should be space for error and correction; therefore, a cycle of iterative actions or activities is possible after the dissemination, reaching the ultimate business performance.

Also, Hallikainen et al. (2020) state that predictive analysis helps companies avoid costly errors. The findings confirm that marketers, during the dissemination phase, can better manipulate the marketing mix if they are provided with predictive analysis, i.e., new market trends and customer future preferences.

4.4.4 Marketing Mix

Despite some studies have posed a question of the adequacy of the marketing mix model during current technological complexities and the social media context (Perera and Hewege, 2016; Schlee and Harich, 2010; Tapscott, 2000; Whitehurst, 2016; Philip et al., 2018), this study’s findings proved the contrary that applying a complete marketing mix of 4 P's is effective to maintain competitive advantage. Keeping in mind that some elements of People, Physical evidence and Process of the 7P's marketing mix do not impact channel dissemination, thereby not achieving CI best practice.

Digital marketing appeared to support marketing mix with interactivity and personalisation. In particular, BDA had enabled real estate firms to collaborate with communities in UAE. Therefore, a dynamic competitive environment requires a flexible and updated marketing mix of 4 P's (McCarthy, 1968), supported by BDA characteristics that can improve the ability to perform quickly and accurately.

4.4.5 Knowledge-Based View (KBV)

The research findings confirm that knowledge plays a substantial role for marketing experts in order for them to perform with competence and legitimacy. The addition of big data technology has improved their self-consciousness, reflection, and their mental process to initiate the action, which all demonstrates the trilogy of mind theory (Hilgard, 1980), completing the knowledge acquisition of understanding data strategy before any sort of marketing decisions.

Also, intelligence provided from data analytics presents the knowledge needed to achieve a competitive advantage. Knowledge is required to enhance organisational agility (Peñalba et al., 2021; Mao et al., 2015; Nonaka, 2009; Fleisher and Craig, 2004). Furthermore, since academics claim the knowledge is formed from information with practice, the intelligence reports received by practitioners present the information about user's experiences and lifestyle patterns, as well as the relationships between each experience; thus, big data does provide the knowledge about the target customers for marketing stakeholders to achieve effective marketing and competitive strategy. However, it is essential to mention that big data solutions associate data analytics based on decision-makers' selections and intent of CI need; therefore, the insights suggested by machine intelligence are context-aware. As a result, the business will gain a type of intelligence based on the question provided for the machine.

4.4.6 Capability-Based View (CBV)

The findings discussed that core competencies emerged through the organisational process of accumulating and learning how to deploy big data resources and capabilities. The ability to optimise big data based on CI needs, together with the discussion of academics about scanning internal and external resources (Linden and Teece, 2018), brings the discussion of how much a business can provide and manipulate data with the V's characteristics (Hosseinian-Far et al., 2018), thus reflecting the business level of competitivity and personality.

Also, detailed segmentation provides the ability to choose which customer/individual should be targeted or not. In other words, BDA can predict whether a particular customer fits a campaign or is postponed for future marketing campaigns that target different segments. Understanding segments of customers' needs, preferences, and priorities seems to perform as dynamic capabilities, empowering decision-makers with the ability to decide whom to eliminate from the marketing campaign.

Besides having both the literature and findings confirm that BDA supports the knowledge-based view of the business, the discussion of customer segmentation and core competencies touches upon the Capability-Based View (CBV) too while maintaining human analytical skills (Roßmann et al., 2018), supporting the competitive advantage approach (Kumar et al., 2020). In other words, BDA demonstrates both knowledge-Based View (KBV) and the Capability-Based View (CBV) if the employee's analytical skills are carefully sustained.

4.4.7 Action Plan

The literature review has identified that decision-makers intend to receive pertinent information with a reduced probability and uncertainty, and fewer similarities (Adrian, 2017; Norris et al., 2020). Academics consent of intelligence being checked for certainty and confirmed that "high uncertainty" intelligence and reports require further analytics to reduce uncertainty level before sharing the intelligence. However, on the other hand, the study found that practitioners were not concerned with certainty level. They assumed that BI had corrected errors in an earlier CI stage. Thus, they proceed taking actions of marketing activities immediately after receiving the intelligence.

Moreover, despite that Sivarajah et al. (2017) have reported the necessity of receiving pre-emptive analytics to proceed for action, this study has found that marketing activities, based on BDA, can resume through descriptive, prescriptive, and predictive analytics only; A decision-maker, instead, can confirm what is required to do more.

4.5 Chapter Summary

This chapter presented findings from both practitioners and academics interview results. According to participants feedback, key topics have been discussed to help form the artefact model. A gap analysis followed, comparing findings between the interviewee settings, focusing on the difference in structuring the CI process. Finally, a critical discussion took over to bridge between literature review and this study's findings. Next Chapter provides research conclusion.

Chapter 5 - Conclusion

The broader focus of the study addresses competitive intelligence process underpinned by BDA implementation in the real estate (medium to big sized) context in UAE. It provides a purposeful response to the research questions; "What is the relationship between BDA and CI elements and process?" and "What are the benefits of combining BDA tools into the CI process?"

The DSR method met the project’s objectives. It enabled the research to use rich data collected by a representative sample of experts, focus on ideas of potential competitive strategies for the organisations, and to analyse the data in such a way to make it useful for IS planning. Following a summary of key results which touch upon research aims, objectives and questions.

5.1 Research aim achieved

The study aimed to fill the theoretical gap and develop a novel model that encompasses CI process elements along with the adoption of Big Data technology implementation to facilitate an effective decision-making model.

The research aim has been accomplished as the objectives set out to achieve the research aim have been fulfilled. A novel model was constructed to inform the corporate CI process while implementing BDA. In summary, the proposed model was shared with experts in the field of practice of CI and BDA to obtain their views of the model components. Subsequently, a comprehensive model has been constructed addressing relevant contribution of BDA implementation in CI process.

5.2 Research Objectives Achieved

Objective 1: Conduct a thorough literature review to identify existing CI models.

An exploratory literature review was conducted to dig upon the research community relating to the research subject. Several CI models were identified in literature; however, this study was able to highlight the gap in the existing research of no correlation or relation between the CI process and BDA implementation is yet standardised.

Objective 2: Identify the common elements of CI process components through narrative extraction.

By synthesising the key themes and keywords as well as considering the reviewed models collectively, this study has helped solicit common elements of the proposed CI process, and it has been listed in section (2.11.2). The findings, demonstrated by the final CCIP-BDABM, have illustrated artefacts elements of current CI process in practice. The process elements (artefacts) are:

1. CI need identification
2. Data strategy recognition
3. Utilisation of data sources and types
4. Employment of big data collection, capturing, storing, sorting, analysis and automation
5. Flexible approach to manual data analytics
6. Knowledge sharing through marketing status reporting
7. Strategical and tactical marketing decisions implementation
8. Delegations through channels dissemination
9. Marketing mix monitoring and evaluation
10. Update deliverables and marketing approach

Objective 3: Construct the preliminary model integrating both BDA and CI together.

The CCIP-BDABM has been developed demonstrating the role of BI department and marketing department towards achieving the needed CI. Data management including the analytics, has been the responsibility of data scientists and data analysts; they provide BDA to the marketing department to resume the CI sequenced activities. The CI integrates BDA to provide a meaningful report, in which, marketing head can form and provide marketing decisions based on it.

Objective 4: To elicit selected experts' perspectives and input following iterative cycles of interviews, and to validate model updates, as part of the DSR methodology.

Objective 5: Construct the final model approved by all participants.

Objective 6: Disseminate results of the new constructed model to practitioners.

Answering Objective 4,5 and 6 collectively, the research methodology followed a qualitative approach by seeking iterative interview cycles to evaluate the CI process. The intention was to design CI principles and build an artefact model that seems most appropriate to the research context. Based on the literature review, the proposed model has implied the nature of the incomplete process in real-life scenarios. The study had justified the necessity to use DSR methodology of iterative interviews with experts to provide solutions for the problem domain. The research succeeded in constructing a tangible socio-technological final model approved by all participants, presenting an IS discipline artefact that can be extended and disseminated to practitioners.

The DSRP activities applied for this study are summarised below:

First, most companies in UAE, particularly Dubai, are investing in a technological solution to support business performance. BDA is the new trend among technological business solutions because of the high level of competitiveness in the market. Thus, many firms in the real estate sector have started investing in BDA to strengthen their competitive advantage. However, without a formal measure on applying BDA towards the competitive intelligence process, it would risk the success of this investment. Accordingly, a literature review was conducted looking for existing models related to the context. The research problem was identified as having no comprehensive model encompassing the CI process while utilising BDA capable of supporting decision-makers.

Second, identified objectives of a solution by providing an artefact model to fill the research gap, and provide guidance for the corporate settings implementations. The conceptual process is consistent with prior literature, building CI components upon most commonly identified in the literature.

Third, the CI and BDA literature was used to design necessary elements integrating BDA into CI process. The sequence of CI process was obtained from CI literature, which served as the theoretical foundation for the development of the artefact solution of the proposed CCI-BDABM.

Fourth, assessing the proposed CCIP-BDABM by approaching experts through semi-structured interviews to demonstrate the process feasibility and efficacy.

Fifth, The CCIP-BDABM has been through critical review and feedback by the leading experts in its intended user community, and a subsequent alteration, including new additions, amendments, and deletions. The proposed model has also been assessed against the model's four fundamentals (in chapter 1), and the outcome of the assessment is that CCIP-BDABM meets the requirements.

5.3 Research Questions addressed

To achieve the research aims and objectives, the following two research questions were sought to be answered:

1. What is the relationship between BDA and CI process in a dynamic competitive environment?
2. What are the benefits of combining BDA tools into the CI process?

Question one has been answered through the demonstration of CCIP-BDABM, which has confirmed the nature of the relationship between CI and BDA. The technological solution of BDA is the core and a necessary element in the CI process in order to achieve successful business performance and strong competitive advantage in a fiercely competitive environment.

Question two has been answered through the demonstration and evaluation of the CCIP-BDABM, revealing several benefits of combining CI and BDA:

- Observe consumers patterns and market trends
- Achieve customised customer's segments

- Decision-making is empowered with a variety of report types.
- Adaptation to the competitive environment
- Tailor product offering
- Most importantly, competitive intelligence has become dynamic, systematic, and competent.

5.4 Research Contributions

This study provides an overview of how current businesses coordinate internal capabilities of big data technology to achieve the desired competitive advantage. The CCIP-BDABM demonstrates how BDA is used as a tool to provide knowledge to decision-makers.

Since knowledge and internal capabilities control organisational agility (Mao et al., 2015), that can adapt to the rapidly changing environments (Linden and Teece, 2018); the model demonstrates how BDA, if employed sequentially within planned time management, can sustain the competitive advantage.

The model clearly lists stakeholders involved in the CI process and highlights the decision-making level required and when. This presentation comprises a booklet for practice and theory.

Decision-maker’s required characteristics are summarised by the ability to strategise, decide (Holmland, 2020), influence CI (Adrian, 2017), manage process timeline, and reflect new marketing mix inputs.

The study generates a new perspective on how to approach the competitive environment. Users (customers) of the digital platforms are a fundamental asset, if correctly segmented, to monitor the competitive environment. Customer's segments extend to more detailed features, which allows marketers to manipulate the marketing mix. This content:

1. Organisations must maintain an excellent digital experience
2. Organisations must not neglect the digital marketing data sources

Hereafter, in the event of CI while BDA implementation, following the research contributes to professional practice and knowledge.

5.4.1 Contribution to Professional Practice

The real estate industry faces problems of fierce competition in the UAE due to a variety of political, economic, touristic and social reasons (Anon, 2017). BDA is the new investment that promises of business growth and profitability. Since there does not exist a formal comprehensive measure to support the step-by-step implementation, this research has made a significant and novel contribution to the marketing field nowadays.

The findings benefit marketers who use or intend to apply BDA as a supporting tool achieving successful competitive advantage by following a uniform CI approach. The research significance of identifying best practices of the CI process and BDA implementation helps organisations identify their own appropriate resources and tools of BDA to utilise within a strategical and operational process of CI. From the decision-making perspective, this research provides guidance on managing and linking CI and BDA operations within an efficient time scale to achieve business and marketing objectives.

5.4.2 Contribution to Knowledge

The subject of competitive intelligence is a constant area of investigation for researchers (Chakraborti and Dey, 2019). However, the scope of the CI process while implementing BDA is a developing subject. The use of DSR in this study for creating a new innovative model combining CI and BDA makes a novel and significant contribution to the theory.

The research has synthesised, harmonised and built upon the existing models to produce the first process model that has BDA integrated into CI process. No such model previously existed in the literature. The CCIP-BDABM is comprehensive and covers the entire CI process from start to end. It includes the logical processing activities addressed in the literature, adding updated terminology of terms as commonly used by community experts.
To summarise contribution to knowledge:

1. Providing a gap analysis between findings based on both corporate and academic settings.
2. The application of DSR methodology for creating a conceptual artefact which are not available in the literature review. Accordingly, it is a methodological novelty contribution to knowledge.
3. The actual artefact which provides an actual presentation of CI and BDA relationship, and how they correlate with each other in a business setup.

5.5 Future Work

Although the CCIP-BDABM provides a comprehensive overview of current business practice, it predominantly focuses on interviewing participants from the “real estate industry”. Future work entails Quantitative work to objectively collect and analyse numerical data through a survey distributed to a large population sample of CI experts from different industries. Criteria of sampling remain the same of experts who are at the level of decision making towards CI. The work context shall extend to other industries like medical, education, telecommunication and FMCG.

Also, engaging in a prototype experiment in the real estate context for one or multiple case studies can confirm the model’s elements and process. Test all aspects of the model, and ensure all questions are answered. This method can determine the adequacy of the model as a solution for the research problem highlighted earlier.

Based on the findings of this study, the DSRP strategy showed a very promising method for conducting research that is beneficial for both theory and practice. It was useful in the research of competitive intelligence area and could be used in other marketing topics and aspects. Another future research activity is to get DSR approach wider to the research communities of the marketing domain; The researcher intends to write and publish several papers that could be used in conferences and seminars. This will help more discussion and construction of related projects.

5.6 Limitations

A qualitative survey of a wider group would have benefited the research scope. However, DSR has potentially limited this aspect. Also, finding an appropriate number of participants who agree on several iterative interviews was a challenge to achieve, especially that the purposive sampling was targeted to decision-makers, in which their time schedule is tight, and sometimes it is unpredicted due to urgent meetings that could be raised.

Moreover, the restriction and inability to run a face-to-face interview, due to COVID-19 pandemic, had limited the social interaction between researcher and participants. However, this aspect provided a strength for the researcher to introduce the flexibility of virtual meetings, which can be more elastic to fit participants' busy day schedule, spotting a time to perform interviews directly from their workplace.

Finally, the limited time provided to complete this study has restricted the option of using a mixed-method approach, and accordingly, the researcher had to narrow down the research scope of aims and objectives, to obtain qualitative results that describe the process rather than measure it.

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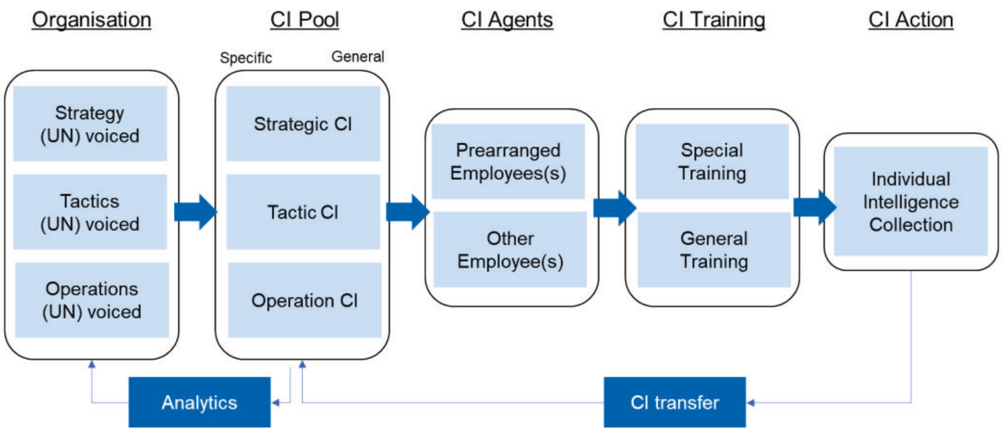
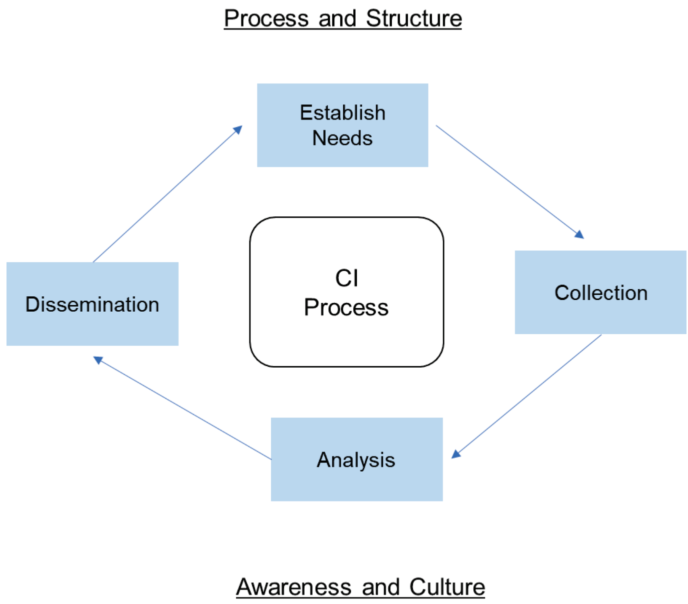
Appendix List

Appendix A – CI Model



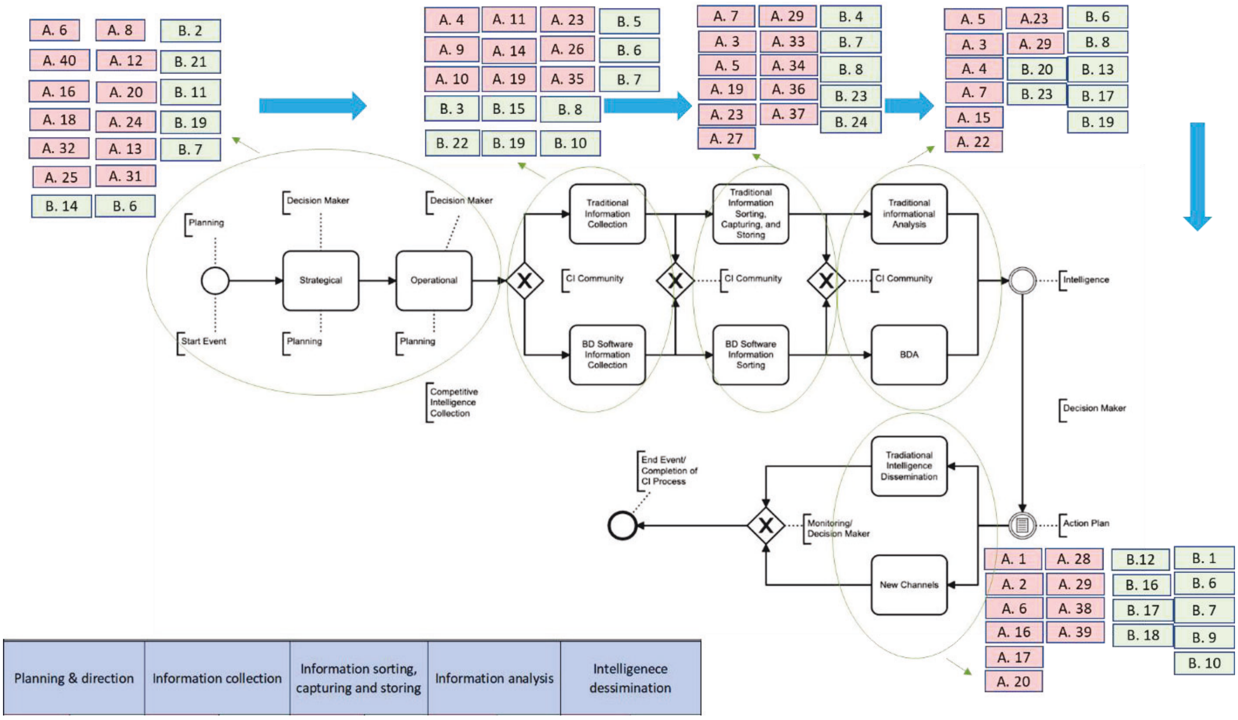
Competitive intelligence model, adopted by Köseoglu et al. (2019).

Appendix B – CI Cycle



Competitive intelligence cycle, adopted from Saayman et al. 2008, adapted from Kahaner (1996).

Appendix C – Literature Review Coding



Manual thematic analysis of key themes and key words from the literature review, which has been distributed among the cycles of CI.

The bellow screen shots are the themes of CI and BDA topics. Themes have performed as a group, in which each group demonstrate main topics of each of the CI cycles.

Topic: CI

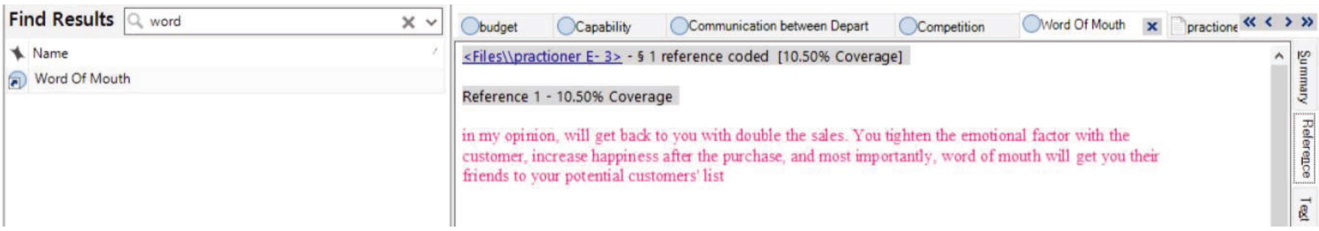
	Initial Theme	NO.	Citation
	Impact	A.1	Hevner 2016
	Actionalble Intelligence	A.2	Tawodzera 2018
	talent management	A3	Thunnissen 2016, Gallardo Gallardo et al 2020
	competency	A4	Ross 2013, Lewis and Hechman 2006, Cappelli and Keller 2014
	skills	A5	Tawodzera 2018
	Esitimative analysis	A6	Tawodzera 2018
	adaptable	A7	Garners model
	diversified strategies	A8	Alexandre 2013
	environmental classification	A9	VRIN framework
	competitors	A10	Degerstedt 2015
	customer feedback	A11	Degerstedt 2015
environment	photos	A12	Degerstedt 2015
	competition threats	A13	Iwu James et al 2020
	unexpected circumstances	A14	Sewdass 2012
	SWOT	A15	Albert Humphrey
	growth and profitability	A16	
	culture	A17	sabri 2019
	product replicability	A18	Teece et al 1997
	flexibility	A19	
	new entry market	A20	Linden and Teece 2018
	choice	A21	
	prediction	A22	
	decision making support	A23	Ricardo et al 2019
	operational decisions	A24	Gilad and Gilda 1988
	strategic decisions	A25	Gilad and Gilda 1988
	specialist knowledge	A26	Koseoglua et al 2019
knowledge	knowledge formation	A27	Cohen and Olsen 2015
	knowledge dissemination & sharing	A28	Ghasemaghaei 2019
	supervision	A29	Dilanian and Howard 2020
	choice	A30	decision maling conceptual model
	data history	A31	decision maling conceptual model
	planning	A32	
	data collection	A33	
	sorting data	A34	
CI process	capturing data	A35	CI process model (pellissier and nenzhelele, 2013)
	storing data	A36	
	data analysis	A37	
	dessimination	A38	
	feedback	A39	
	influential factors	A40	Van Den Berg el al 2020

Themes related to CI extracted from the literature review

Topic: Big Data	Theme	NO.	Citation
volume	data amount	B.1	
variety	data sources	B.2	
velocity	data speed	B.3	
veracity	uncertainity of data	B.4	
value	valuable insights	B.5	
	IT infrustructure	B.6	Barney 1991
	organisational ability	B.7	Lu and Ramamurthy 2011
	capability	B.8	Dynamic capability
	innovative performance	B.9	
	unexplored apportunities	B.10	calvard 2016
	customer satisfaction	B.11	
	product offering	B.12	
	analytical skills	B.13	Robbmann et al 2018
	identify objectives	B.14	Ghasemaghaei and Calic 2020
Descriptive analytics what has ahhpened	data history	B.15	yasmin et al 2020
inquisitive analytics why it happened	probabilities	B.16	Ghasemaghaei 2018
perspective analytics what could happen	prediction	B.17	
prescriptive analytics what to do	recommendations	B.18	
	indicators	B.19	Islam et al 2015
pre-emptive analytics what is required to do more	preventive insights	B.20	Sivarajah et al 2017
	visual context	B.21	Louridas and Ebert 2013
	customer demand	B.22	Gavin 2019
	IT standards	B.23	
	information flow	B.24	Khan 2020

Themes related to BD extracted from the literature review

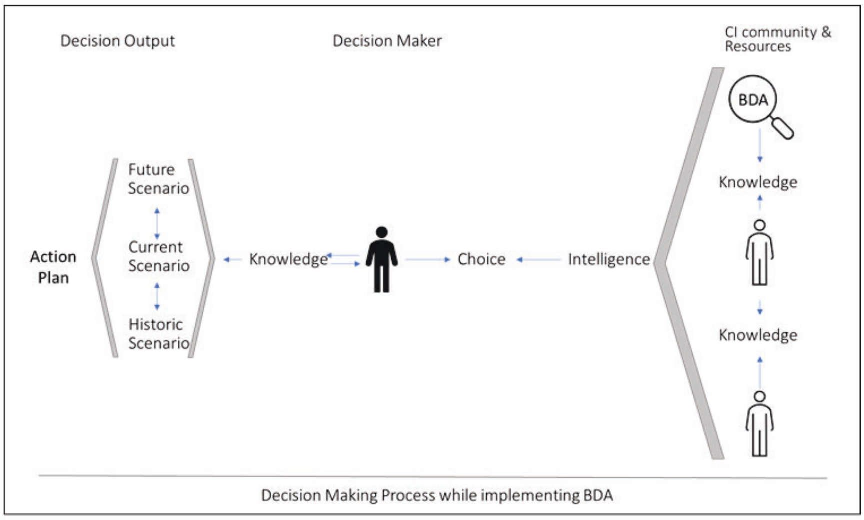
Appendix D – Word of Mouth



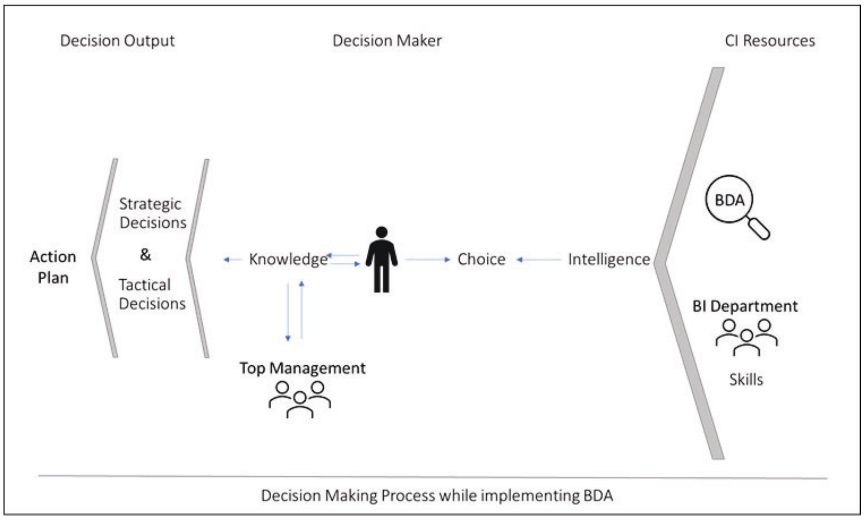
Word of mouth (Code) in the Nvivo analysis, for practitioner E

Appendix E – Decision Making

Conceptualized Process based on literature review



Process based on research findings



Decision-Making Process comparison between conceptualised and final model after the findings.

Appendix F - Promotion

practioner C | practioner D | practioner E- | Promotions | Promotions - Coding by Item

<Files\\practioner B> - § 2 references coded [4.39% Coverage]

Reference 1 - 2.03% Coverage

During execution, I could pause a promotion in one channel and instead invest more in another promotion through onther channel that brings us better results... If needed, I would stop or exclude using a particular user category that is not making money for us; for example a female of the age 18-24 are not my user interest to buy properties because they simply do not have the purchasing power so we target male instead.

Reference 2 - 2.36% Coverage

The intelligence is very effective. And even if I'm not using digital marketing campaign Let's say I'm running event. I'm running a roadshow. Sponsorship outdoor signage. Flyers. I will be able even to design. The content of these activities. The content is based on intelligence. The content most of the time must include a capturing words which presents some promotions and offers, that we already know that this type of offer is most likely to be effective for this particular category.

<Files\\practitioner A> - § 1 reference coded [0.90% Coverage]

Reference 1 - 0.90% Coverage

honestly im always overwhelmed. because there is a new tool they want to suggest to you. But this Sales Force has generated a very good platform for business. And much more automating promotions and good process imagine how it can accelerate your deliverable and meeting up sales target.

<Files\\practioner C> - § 1 reference coded [1.49% Coverage]

Reference 1 - 1.49% Coverage

Not verbally, of course. Yeah. I need to present statistics. The business before. The business goal. And where the business is heading. On parallel, I need to put my numbers of prices and targeted offers and discounts which I believe it is achievable based on the intelligence provided to me,. Shareholders Are interested in numbers.

<Files\\practioner D> - § 1 reference coded [2.59% Coverage]

Reference 1 - 2.59% Coverage

In order to be able to compete in UAE market, we look forward to be able to provide the most wanted offers for our current and expected customers. Without adequate understanding of customer's data, this objective might not be possible. For example

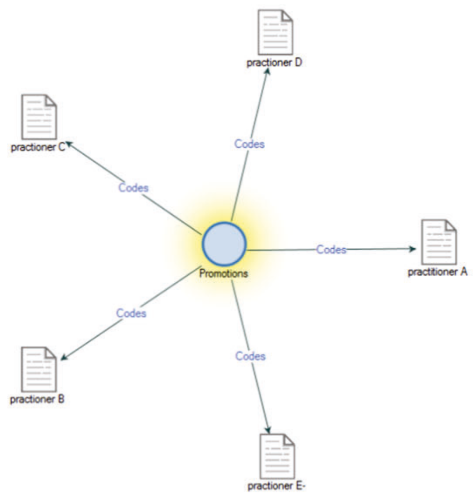
<Files\\practioner E-> - § 2 references coded [27.16% Coverage]

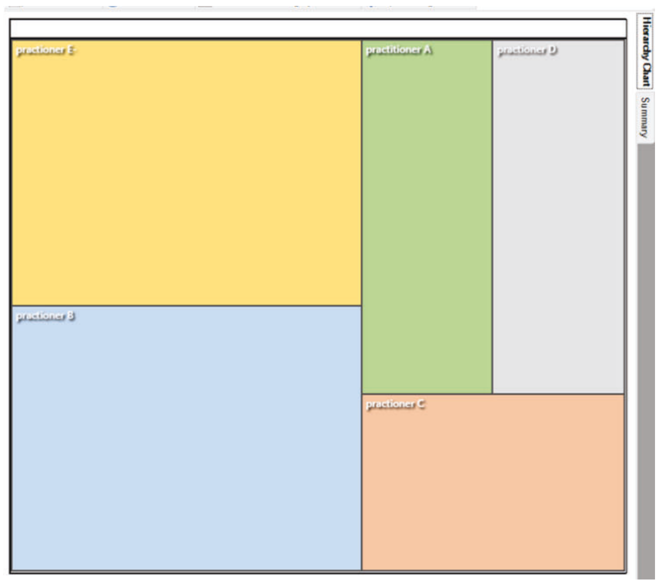
Reference 1 - 20.09% Coverage

we are going through massive digital transformation, both internally and externally. For the internally. The internally is about having our systems automated in a fashion that artifitial intelligence can get data for us, and not to have to insert it manually for us every month. Externally, we ;launched our agents applications. So today our agents are able to see our inventory, sales of agreement , mortgage calculations,that calculate how much a customer is welling to pay based on our offers and promotions.

Reference 2 - 7.08% Coverage

the ease of suggesting prices and Changning these pricess according to internal reasons or according to the market and customers have helped our name to be dominant in this market.



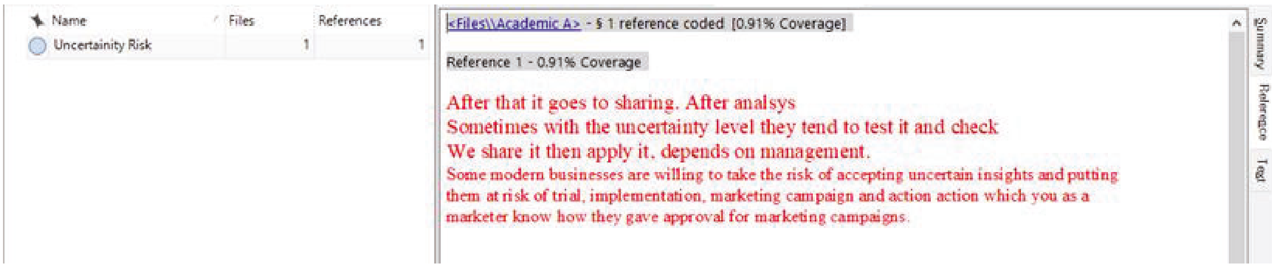


Nvivo analysis of “Promotion” code: All practitioners consent on promotion importance from different angles.

Appendix G - Promotion

Nvivo analysis showing comparison between each of the marketing Mix P's (nodes) compared to a one node (Promotion). The analysis shows that Promotion is the most discussed by all practitioners

Appendix H – Uncertainty Risk



Academic A discussing analysis uncertainty risk

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Appendix I – First Round Questionnaire

Questionnaire A) First Round of Interviews

Please notice: any personal information provided will be kept confidential and will be deleted once the comments and feedback have been reviewed and analysed.

Before proceeding to the questions, please state:
Your full name: ____
The institution you work/ have worked for: ______________________________
Your job title(s): ____
Qualification and years of experience: ______________________________
____

CCIP-BDABM model

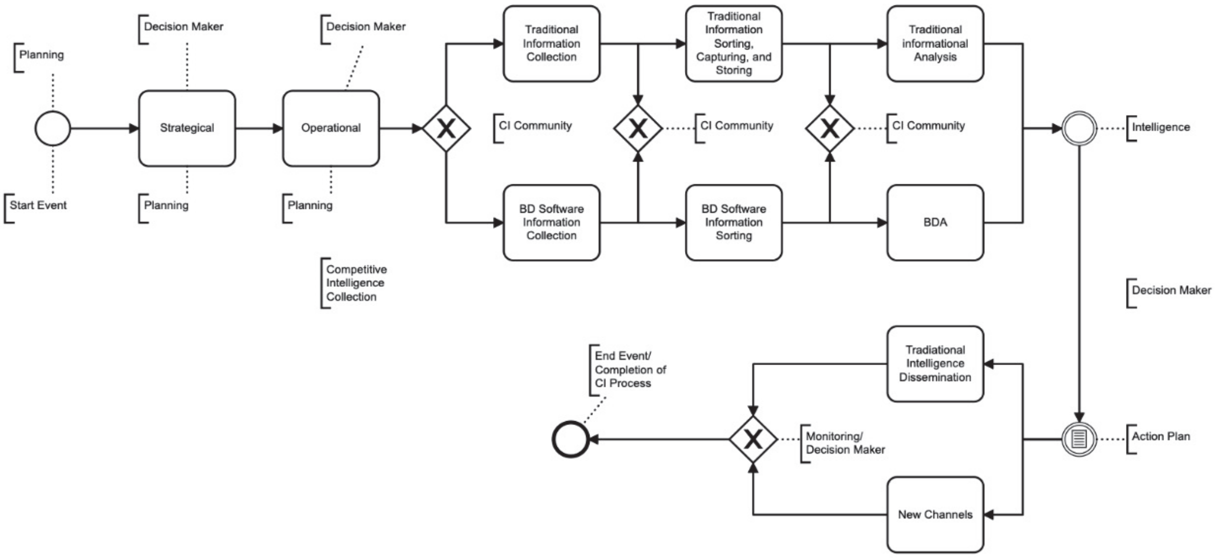
Comprehensive Competitive Intelligence Process- BDA Based Model

This research project titled "Design Science Research Approach Towards the Construction of Competitive Intelligence Process Framework in the Era of Big Data". It aims to explore how BDA can be integrated into competitive intelligence process achieving best practice of business performance through sufficient decision-making structure.

Competitive intelligence is a series of data processing of high-value information about competitive areas, which is transmitted at the right time to decision-makers to make action plan that enhances the business competitive advantage.

So, in order for this research to be able to verify main effective elements of competitive intelligence process and provide rich description of BDA and other components which can lead to the optimum cycles of the CI process, the CCIP-BDABM model is introduced to help for this verification.

The variables, nodes, and connections between the nodes within this model are put together following an extensive review of existing studies that have assessed competitive intelligence cycles and big data integration.
The model focuses on the competitive intelligence process from the marketing operational perspective only. It explains when decision maker takes part, and how the marketing community operate the process from the starting point of initiating the plan, until accomplishing the purpose of the competitive intelligence. A few instances of the factors that are excluded from my study scope are regulations, sustainability and financial aspects, in which any correlation leads to it is not related to this research subject.



In reviewing CCIP-BDABM model:

1. Do you agree that Competitive Intelligence process starts with *planning*?

2. Is there a Competitive Intelligence process in your organisation? Please describe who initiates the Competitive Intelligence process in your organisation?

3. is it necessary, in the CI planning phase, to have both strategical and tactical decisions and directions?

4. Please explain what type of data your organisation normally collects, and who usually

   collects it?

5. Would you say sorting, capturing and storing the collected data are possible through BDA software with minimal human interactions?

6. What could be the team’s obstacles during sorting, capturing and sorting data collected?

7. what type of Competitive Intelligence reports does your organisation seek for? Why?

8. Is there still a need for traditional data analysis? Why? If yes, in what cisrumctances that would be required?

9. If data analysis can be taken over by BDA software, which department is responsible for such analysis? How large is that department compared to other departments within the organisation? (The answer could be approximate and either in financial terms of HR FTE)

10. What happens after Competitive Intelligence reports are ready?

11. Who is the key decision maker(s) for the Competitive Intelligence processes within your organisation?

12. How important is the support from top management? And when is it mostly important?

13. Please identify any elements in the model that does not actually occur in practice.

14. Please describe which activities in the model are most closely related to your field of practice and your own experience?

15. Please provide any additional comments that you might have on the model attached.

16. Did you think that the model adequately represents the competitive intelligence flow while integrating BDA? If you would like to change, what will need changing?

Appendix J - Second Round Questionnaire

Second Round Interviews

CCIP-BDABM model proposed

After First Interviews Round

Comprehensive Competitive Intelligence Process- BDA Based Model

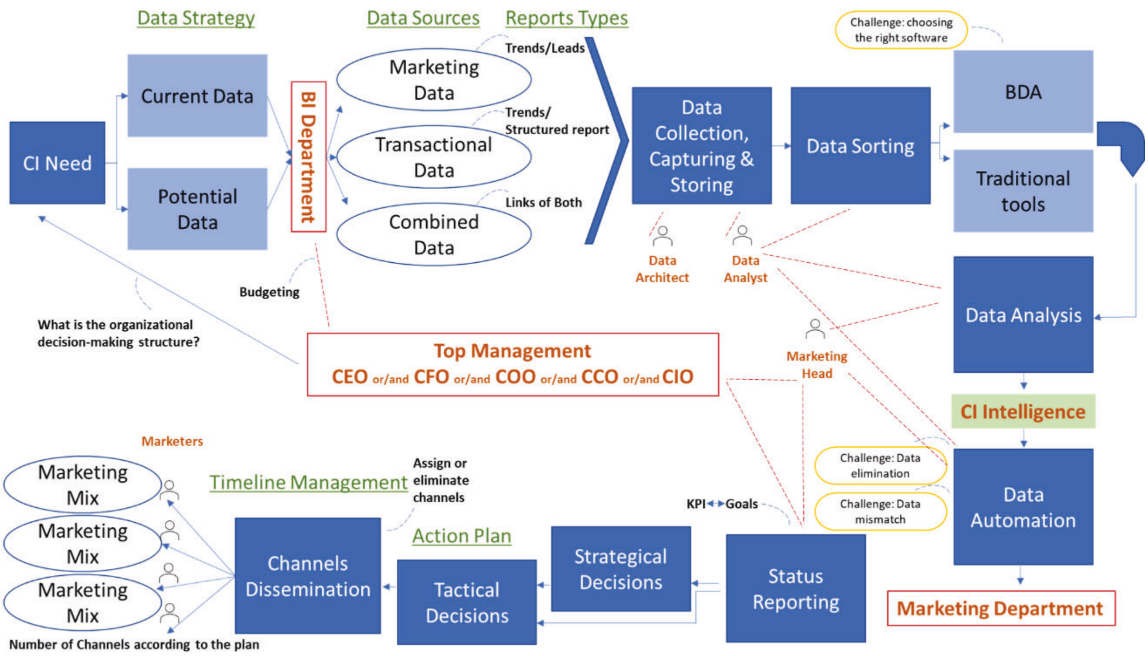
Answers of all first interviews were analysed and reviewed and based on these answers; this draft model (bellow) is formed.

The Competitive Intelligence process in the era of BDA utilisations starts with identifying CI Needs. What is needed to gain a competitive advantage?.

Following the Need, the Data Strategy takes place through two pillars: Current Data & Potential Data. BI department is responsible for the Data Strategy, in which it will define what Data Sources to approach for the desired Intelligence Need. each Data Source is recognised by the type of reports it can provide.

Big Data Activities starts through multiple phases. First is collecting, Capturing & Storing Data. Next is Data Sorting. Both activities have the data architect and data analyst involved.
The Analytics phase starts after, usually through BDA, and traditional analytics if needed. The output reports of this phase are the Needed Intelligence. Data Analyst and Marketing Head are on top of this phase.
After receiving the Intelligence reports, (marketing) Data Automation is followed. The Marketing Head is responsible for defining this activity's directions.
Having all Data Reports Set and ready with the desired Intelligence, Status Report is prepared by Marketing Head and discussed with Top Management. Directions after this discussion will continue to Strategical and Tactical decisions of the marketing campaign. Ad-Hoc campaigns are sometimes expected; therefore, Tactical decisions can be directly approached, skipping Strategical decisions.

Channel Dissemination will proceed in distributing responsibilities for marketers. Each marketer look after their designated marketing channel and should be monitoring the marketing mix.
Time Management is critical at the last phase, as Top Management has expectations of deliverables within a scheduled timetable.



<u>In reviewing CCIP-BDABM model:</u>

17. Do you agree that Competitive Intelligence process starts with CI Need?

18. Do you agree on the Data Strategy being a responsibility of BI department only?

19. Is the sequence of Big Data activities, correct?

20. The marketing department is involved after status reporting, and marketing head is responsible for this activity. Do you agree?

21. Any comments on the strategical and tactical decisions?

22. Does the marketing mix correctly placed in the model, and which factors here are implemented?

Appendix K - Third Round Questionnaire

Third round interviews

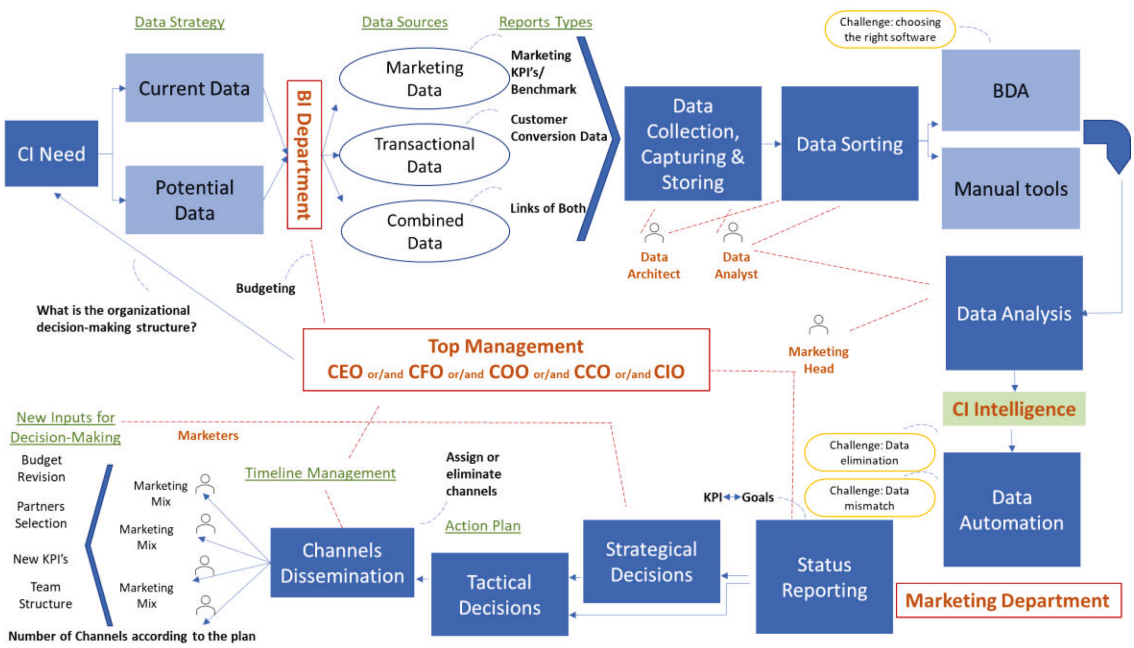
CCIP-BDABM proposed

After Second Interviews Round

Comprehensive Competitive Intelligence Process- BDA Based Model

Answers of all Second interviews were analysed and reviewed and based on these answers; this draft model (bellow) is formed.

Few modifications applied:
Big data report types, new inputs for decision makers after the marketing mix



In reviewing CCIP-BDABM model:

23. Do you agree that Competitive Intelligence process starts with CI Need?

24. Do you agree on the Data Strategy being a responsibility of BI department only?

25. Is the sequence of Big Data activities, correct?

26. The marketing department is involved after status reporting, and marketing head is responsible for this activity. Do you agree?

27. Any comments on the strategical and tactical decisions?

28. Does the marketing mix correctly placed in the model, and which factors here are implemented?