Implementing Data Analytics Marketing Strategies for Not-For-Profit Organisations: Learning from a Case Study in Singapore

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Abstract

Many commercial organisations have used data analytics to understand their customers and provide customised services and products to gain competitive advantages. Some of these organisations, like Uber and Amazon, have successfully disrupted the existing market leaders and forced the incumbents to change their business models.

Although data analytics strategies provide new opportunities for organisations, there are tremendous technical and organisational challenges for companies to implement the strategies successfully. Many organisations have failed in the implementations because they did not manage the changes systematically. Many pieces of research are done, using commercial organisations especially the large ones, to provide recommendations on implementing data analytics strategies successfully. Furthermore, most of the research is performed in the United States and Europe. Research gaps are identified as there is little research work performed for small, not-for-profit organisations in Singapore.

This research project attempts to fill the research gaps, firstly, by understanding the challenges encountered by small, not-for-profit organisations in Singapore when implementing data analytics strategies. Secondly, by providing appropriate recommendations for such organisations to guide them successfully launch data analytics strategies. This is because not-for-profit organisations are becoming more influential, and consuming an increasing proportion of national resources.

Through a case study organisation, the research project identified challenges and success factors for implementing data analytics strategies for not-for-profit organisations. Some of the challenges and success factors differ from those noted in literature reviews, which use large, commercial organisations for research.

Using knowledge gained from literature review and strategy implementation at the case study organisation, a new 5 “Os” framework is proposed to assist small, not-for-profit organisations launch their data analytics strategies. Although this research project focuses on a not-for-profit organisation in Singapore, it is expected that the 5 “Os” framework can be used by organisations outside the country, with appropriate adaptations.

Some observations made during the research work are new to the literature. For example, it is noted during the research work that leaders who understand the importance of digitalisation and data analytics, would find ways to overcome talent shortages and funding issues. These discoveries can be added to the body of knowledge to strengthen the implementation framework, particularly useful for small, not-for-profit organisations.

Despite the exciting findings, it is acknowledged that there are limitations in the research work. For example, due to the small set-up in the case study organisation, future research can be performed on the same topics using other research methodology, such as quantitative and random sampling methods, or using organisations in different geographical locations.

Key words: data analytics, digitalisation, transformation, contextual marketing strategies, change management, not-for-profit organisations, Singapore.

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Chapter 1. Introduction

1.1. Preamble

This research work intends to identify challenges that small, not-for-profit organisations are facing so that appropriate strategy can be devised to assist them in implementing data analytics strategies successfully. This chapter starts with the background in section 1.2, where information about the industrial trends on data analytics and the challenges for implementing data analytics strategies in organisations are deliberated. Section 1.3 outlines the problem statements and research gaps. Section 1.4 examines the purposes and significance of this project, where research questions, research aims, and research objectives are identified. In section 1.5, the research methodology is discussed, and 1.6 summarises the contributions to professional practice and academic knowledge. Section 1.7 investigates the ethics issues, while section 1.8 lists the thesis structure before the summary in section 1.9.

1.2. Background

The current business world is being disrupted by new business models, largely due to digitalisation, where consumers' behaviours are being captured digitally. The data about consumers' behaviours can be analysed to gain insights, which in turn can be used to provide personalised services to a broader group of consumers. As technologies advance rapidly and the world is undergoing digital transformation, start-up companies are using digital strategies, such as data analytics, to create new business models and successfully disrupt conventional business models.

Data analytics is a new information technology tool that allows businesses to collect and analyse data to gain insights and innovate new ways to serve consumers better (Lin, 2014). It can be used to gain valuable insights into customer behaviours, create new business models, and build competitive advantages (Capriotti, 2014). Large commercial organisations, such as Amazon (Wills, 2018) and Mastercard (Hund-Mejean, 2018; Asgeirsson, 2018), use data analytics to gain competitive advantages. Companies, such as Uber, Airbnb, and Netflix, are using data analytics, internet-based business models to revolutionise industries (Hair et al., 2018).

As digital disruption is affecting all industries, geographical areas, and customer experience, and the impacts are not confined to only technology (Gartner, 2018), all businesses are urged to devote time to learn and understand digital revolution and data analytics (Gartner, 2018; Westerman and Bonnet, 2015). However, many existing small and medium-sized organisations face challenges to catch up with digitalisation and reap the benefits of data analytics (OECD, 2017).

1.2.1. Data Analytics Create New Opportunities

As data analytics can create competitive advantages (Lin, 2014), there is a need for organisations to shift their paradigm to translate data into useful business information and redefine their decision-making process to be data-based (Yeo and Carter, 2017). Bump (2015) revealed that data analytics has changed the landscape of her organisation, Massachusetts State Auditor. Similarly, Yeo and Carter (2017) envisaged that there are infinite opportunities for organisations to create new marketing strategies using deeper insight into customer behaviour.

Lin (2014) reported that Amazon analysed data to identify customers' shopping preferences and with the insight, makes personalized recommendations to the customers. This strategy has contributed to one-third of the sales at Amazon. In addition, MasterCard uses the data it possesses to analyse and identify the cardholders' buying patterns to provide personalised offers, which generate customer loyalty (Asgeirsson, 2018). These examples demonstrate that organisations should use data analytics to innovate smart services (Maglio and Lim, 2016).

1.2.2. Better Performing Organisations are More Likely to Use Data Analytics

Leading organisations are using data analytics to innovate and outperform their competitors (Marshall et al., 2015), as top-performing organisations are five times more likely to use data analytics than those who do not (LaValle et al., 2011). As more organisations are using data analytics, the tools become easier to use, and more powerful, which in turn, attract more organisations to adopt data analytics (Hair et al., 2018). Therefore, organisations, who have not started, have little reasons to delay implementing data analytics strategies further.

1.2.3. Technical and Organisational Challenges to Launch Data Analytics Strategies

Although data analytics is enabling businesses to gain insights and turn these insights into opportunities or competitive advantages, not all organisations are successful in implementing data analytics strategies. Below are some of the challenges that avert organisations from successfully launching data analytics strategies.

Technical Challenges – Data Management

Segarra et al., (2016) noted that due to the sheer volume, variety, complexity, and velocity of data being generated, there are challenges in capturing, storing, managing, and analysing the data. Lemieux et al., (2014) established that issues such as data accessibility, data quality, and record-keeping are challenges to implementing data analytics. Similarly, Hair et al., (2018) pointed out that privacy issues and challenges offer both challenges and opportunities to organisations as they develop their analytic capability.

Organisational Challenges - Leadership

McAfee and Brynjolfsson (2012) viewed the use of data analytics as being compatible with the "management revolution" because it involves changes in the value of experience, expertise, and management practices. As such, they opined that leadership is the key to make an organisation becoming data-enabled. Block (2003, pp 331) also concluded that "leadership is at the heart of the change process." Ransbotham et al., (2016) also quoted companies' unwillingness to enhance data management capabilities as a key cause for failures of data analytics projects.

Larson (2018) quoted Gartner's report that the majority of data science and analytics project failed because there was a lack of clear strategy. By the same token, Demirkan and Dal (2014) revealed that lack of clear business needs, value, and clear data analytics strategy are causes for failures.

Organisational Challenges – Understanding the Business and Data

The biggest obstacle to adopting data analytics is not data availability but the lack of linking data analytics to business solutions (LaValle et al., 2011) because analytics must be rooted in the business needs and the context in which the data are being collected (Angrave et al., 2016).

Organisation Challenges – Skill Development and Culture

Most companies failed to achieve sustained success with analytics because they were reluctant with the investment, cultural change, staff skill development, and top management sponsorship (Ransbotham et al, 2016; LaValle et al, 2011).

1.3. Problem Statements

Many companies have failed to launch data analytics strategies because they have not managed changes systematically.

In order to increase the chances of being successful, organisations are recommended to use an integrated approach to drive changes systematically and constructively (Al-Haddad et al., 2015; Tamilarasu, 2012). This should start from the creation of a business case to justify and communicate the benefits to counter resistance throughout the change process (Tamilarasu, 2012). Formulating a simple governance structure to communicate the scope and rationale of changes to gain stakeholders' acceptance is critical (Lam, 2009). The performance monitoring mechanism should also be formulated.

Similarly, McAfee and Brynjolfsson (2012) highlighted that data analytics strategies should start with leadership, where clear goals and success factors should be defined. This is followed by talent management, technology, cross-functional cooperation, and change of culture. Understanding the business and data (Larson, 2018), information governance, and technical innovation (Lemieux et al., 2014) are required to implement data analytics successfully.

Despite many pieces of research work on data implementation strategies, implementing data analytics, which is akin to "management revolution" or change management (McAfee and Brynjolfsson, 2012), the success rate is less than 30% (Al-Haddad et al., 2015). Ransbotham et al., (2016) found that skill development, cultural change, and data management capability are three key causes for failures. They recommended organisations focus on skill development, data development, and cultural norms.

1.3.1. Research Gaps

Based on the literature reviews, most of the research works on data analytics are performed for commercial organisations, especially the large organisations, in the West, namely in the

United States and Europe. The impacts of technologies on not-for-profit organisations are often overlooked (Eusanio and Rosenbaum, 2019), although the purposes and consequences of implementing technologies and data analytics are different for commercial and not-for-profit organisations (Kilbourne and Marshall, 2005).

Acquiring data analytic capability should not be confined to large businesses (Lin, 2014), especially when the influences of not-for-profit organisations on our community are increasing (Newman and Wallender, 1978), there is a need for research works to close the gaps.

Furthermore, "small data" can be used to answer specific questions and add value to organisations (Kitchin and Lauriault, 2015). Therefore, research gaps exist as there are few research works on organisations that do not possess advanced data analytics expertise and to introduce new management tools to address data analytics issues to the corporation (Segarra et al., 2016). Specifically, there are limited research works on data analytics noted for the following segments:

1) Organisations in Singapore, which is in South-East Asia (as most research works are performed in Europe or the USA).
2) Small organisations (as most research works are performed using large organisations).
3) Not-for-profit organisations (as most research works are performed using commercial organisations).

In addition, most of the research works have made wide-ranging recommendations for generic organisations to implement data analytics strategies. They were not specific to any particular organisation and they did not prove that their recommendations would be successful, especially for small, not-for-profit organisations with different structures and constraints. Again, this is one of the research gaps identified by Segarra et al., (2016), who emphasised the need for research works to focus on practical data analytics strategy implementation, especially for organisations that do not have advanced analytics expertise.

1.4. Purposes and Significance of the Study

1.4.1. Research Rationale

As identified in the research gaps, there are limited research works on small, not-for-profit organisations in Singapore. In addition, there are limited research works that prove their recommendations can successfully assist such organisations to implement data analytics strategies. This research work will adopt a case study approach, using a small, not-for-profit organisation in Singapore to identify the challenges and then devise necessary steps to kick start its data analytics strategies.

The organisation to be used for the case study is a small, not-for-profit, professional body in Singapore that intends to improve its member engagement strategies. Specifically, the organisation, ABC, intends to improve its marketing strategies from a "one-size-fits-all" strategy to one that is targeted and customised to the different needs of its members. Marketing of training courses is prioritised for the professional body because training revenue accounts for more than 75% of its annual source of income.

While ABC intends to use data analytics to launch targeted, contextual marketing for its training courses, it needs help as it has limited skills and know-how. This research work will start by identifying the challenges and constraints that the organisation is facing. This will be followed by devising appropriate steps to help the professional body overcomes those challenges and constraints so that it can successfully launch its data analytics-based marketing strategy. In the course of its implementation, it is expected that the lessons learnt will be added to the knowledge base for other small organisations that intend to do the same.

In summary, this research work attempts to fill the research gaps in at least three ways. Firstly, it will fill the gaps in limited research works on implementing data analytics strategies for small, not-for-profit organisations. Secondly, it will contribute to the literature and the limited work in this context in Singapore. Thirdly, by using a case study approach and devising steps to implement data analytics strategies, it will offer practical recommendations specific to small, not-for-profit organisations.

1.4.2. Research Questions

Considering the research gaps and the research rationale outlined above, this research project targets to answer the following research questions:

1) What are the challenges and constraints to implementing data analytics strategies in small, not-for-profit organisations in Singapore?
2) How can small, not-for-profit organisations in Singapore, with limited know-how and resources, successfully implement data analytics strategies?

1.4.3. Research Aims

This research project aims to:

1) Identify challenges and constraints to implement data analytics strategies in small, not-for-profit organisations.
2) Evaluate options and provide suitable advice to implement data-driven, contextual marketing strategies for small, not-for-profit organisations.

1.4.4. Research Objectives

The research objectives are:

1) Ascertain challenges and causes for failures to implement data analytics strategies, through the performance of a comprehensive literature review.
2) Analyse key challenges to implementing data analytics strategies confronting the not-for-profit organisation, in Singapore, with limited resources and know-how, through interviews and review of archival records.
3) Identify the required information in the member's database that is required to devise segmentation and contextual marketing strategies.
4) Recommend suitable data analytics tools to implement data-driven, contextual marketing strategies for the small, not-for-profit organisation, bearing in mind the challenges and constraints confronting the organisation.
5) Formulate a change management plan to transform the "one-size fit all" marketing strategy into data-driven, contextual marketing strategies.
6) Through reflection, thoroughly review the drawbacks and provide recommendations for small organisations to enhance their implementation strategies.

1.5. Methodology of the Study

1.5.1. Research Philosophy, Methods and Data Collection

This research project involves identifying challenges and formulating change management to improve an organisation's strategy; therefore, it involves changes in culture, staff mindset, data management, and processes of the organisation. These factors are dependent on the people, especially the leaders, of the organisation, therefore, the research student opines that there is no "single truth". In addition, this transformation is similar to "change management" that must be properly planned. As concluded by Al-Haddad et al., (2015), the method of change must be adapted and aligned with the organisational change type. Hence, there is no "single true way" to manage change.

The research student is adopting subjectivist ontology and interpretivist epistemology as there is no "single truth" in the research topics. Qualitative methodology, with a case study design, is adopted for the research project, which attempts to deep dive into the not-for-profit organisation in Singapore to uncover the "unknown".

Being an active volunteer of the not-for-profit organisation used for the case study, the research student is considered a practitioner-researcher, and this research work involved research using practical experience. It is envisaged that lessons learnt through practical research can contribute to both professional practice and the body of knowledge (Coghlan and Shani, 2014; Coghlan, 2003). Further, Raelin (2015) and Costley et al., (2010) encouraged learning to be acquired in practice. The interview is adopted as the main data collection method and it is supplemented and validated by information collated through archival records, where appropriate.

1.5.2. Research Methods

The research project aims to identify challenges and propose appropriate means to implement data analytics strategies for not-for-profit organisations with limited know-how and resources. It is using a not-for-profit organisation, ABC, in Singapore as a case study organisation. The case study is research using one single unit for intensive study and aims to generalise across a wider context (Gerring, 2004), and it is a valuable research method (Tellis, 1997). Therefore, lessons learnt from this case study research project will be valuable for other similar not-for-profit organisations that intend to do the same.

1.6. Contribution to professional practice and academic knowledge

As discussed in the research rationale section, this research work attempts to fill the research gaps in at least three ways. Firstly, it contributes to the academic literature on researching data analytics implementations in Singapore's context. Secondly, it fills the gaps of limited academic researches on implementing data analytics strategies for small, not-for-profit organisations. Thirdly, by using a case study approach to help the organisation to implement data analytics strategies, it offers practical recommendations to other small, not-for-profit organisations with a similar setup. In summary, this research work can contribute to both academic and professional bodies of knowledge.

1.7. Ethical Considerations

1.7.1. Insider Researcher

This research project is using one organisation, where the research student is an active volunteer, as a case study. Staff employed by the organisation will be recruited to participate in the project, where they will be interviewed. However, it is noted that as a volunteer, the research student's role is to set strategic directions for the not-for-profit organisation. There is no executive authority vested in the research student, who does not conduct performance appraisal nor has any influence on the staff's remuneration. This mitigates the potential conflict of interest and pressure for the staff to participate in the research project. Therefore, the staff, who are not vulnerable participants, have no fear of being coerced into participation.

As an insider-researcher, Unluer (2012) quoted constraints such as overlooking routine behaviours, making invalid assumptions, and ethical issues. Greene (2014) however, proposed the following techniques to avoid the pitfalls:

1) Triangulation – by obtaining information and evidence from different sources. Archival records are used, where appropriate, to validate information obtained via interviews.
2) Reflexivity – researchers should be aware that the field and audience influence the researchers, hence manage the conditions actively (Mahadevan, 2011).
3) Information collected for this research work will be used only for research purposes. This will avoid ethical issues such as conflict of interest and confidentiality.

In addition, due considerations are given to factors such as benefits and harms, informed consent, and confidentiality.

1.7.2. Benefit and Harm

The research project is beneficial to all the parties involved in the project:

1) The case study company can formulate an implementation plan to adopt a more advanced marketing strategy using data analytics;

2) The participants can learn "future skills" in data analytics and change management approaches. In the long run, the research project is expected to reduce manual work and lighten their workload.
3) The project sponsors as the implementation of the data analytics strategy demonstrate their leadership skills.
4) The research student will acquire research skills. In addition, he will acquire leadership and change management skills to implement data analytics.
5) The community can leverage the lessons learnt from the case study to implement data analytics strategies.

There are common interests among the stakeholders and ABC to make sure this research project is successful. There is no obvious, foreseeable conflict of interest among the case study organisation, participants, and the research student.

In this project, the communication is open and transparent without deception. While it is expected that this research project should not harm the participants, the manner of asking questions may make some of the participants feel stressed, intrusive or offensive. Therefore, mutual respect is maintained to avoid such situations.

1.7.3. Informed Consent

The purposes and objectives of this project were explained to all the participants. They were given time and opportunity to clarify, ask questions, and think about the value of the research before they gave their consent.

Before the semi-structured interviews were conducted, it was made clear to the participants that they could stop answering any question if they did not feel comfortable. Their rights to reject the voice recording of their interviews were highlighted before the interviews. In addition, they were briefed on their rights to withdraw from the project. None of the participants has exercised their rights to avoid the questions, reject voice recording and withdraw from the interviews.

Research student acknowledges that practical research is political (Coghlan and Shani 2005), therefore the research student needs to be politically astute. As this project is undertaken with mutual benefits, the research is conducted in the spirit of collaboration. The participants are expected to acquire new skills in data analytics implementation for the organisation and they are expected to reduce their tedious and manual work after the implementation.

In this mutually beneficial project, the participants are treated as equal partners. As recommended by Coghlan and Shani (2005), the roles and expectations were clarified upfront to build trust for the participants to willingly engage in the project. The participants were informed of the objectives and the purposes of the project and information collected, as advocated by Costley et al. (2010).

In addition, as suggested by Coghlan and Shani (2005), the research student allowed clarification about the roles and expectations during the process.

During the research project, the participants and the research student maintained very cordial, respectful, and equal working partnerships. The research student expects this working partnership with the participants to continue, even after the completion of the project.

1.7.4. Confidentiality

There are two groups of data that are being used for this research project:

- Interviews with participants
- Membership information that is used for analysis to devise data-driven, targeted, and contextual marketing.

Both sets of information will be stored in a computer with password protection and updated antivirus software (McAfee). The information collected during this project is used only for research purposes. No information will be used for other purposes and none will be shared with a third party.

The names of the participants will not be revealed in any of the reports or publications. Their names are “coded” to ensure anonymity when stored on the computer.

For research works involving small team sizes, Olivier (2009) proposed that confidentiality should be discussed with the participants to reduce the chances of breaking confidentiality. Olivier (2009) stressed that confidentiality should be discussed repeatedly, such as during recruitment, periodically over the life of the research project, and the final session.

Furthermore, it is highlighted to the participants that confidentiality should be maintained if they leave the organisation and after the project. Recommendations by Olivier (2009) are strategies adopted by the research student when undertaking primary data collection.

Petrova et al., (2014) emphasised that building trustful relationships is essential, especially in qualitative research. The research student performed the following during various stages of the research project, as proposed by Petrova et al., (2014):

1) During the participants' recruitment stage, the research student clarified the purpose of the research project and highlighted the importance of maintaining confidentiality. The research student also clarified the process to obtain informed consent.
2) During data collection, the research student re-emphasised the importance of confidentiality. Due to COVID-19 pandemics, physical meetings were not allowed. All interviews were conducted via Zoom meetings, where passwords were set to maintain confidentiality, away from ear-dropping and disturbance. The interviews were audiotaped, with the consent of participants, and only the research student has access to the audiotape.
3) During transcription and data analysis, the research student sent all the transcripts to the participants for validation. After the analyses of the transcripts, the findings were grouped into themes. Thesecond round of interviews was conducted with the participants to confirm their understanding.
4) The participants' names are coded to protect their confidentiality.
5) During the dissemination of research results, participants' identifying information is coded. In addition, a gender-free term, e.g., the male pronoun is used regardless of their actual gender.
6) Information about the participants will not be shared unless permission is granted in writing.

The second group of data relates to members of the not-for-profit organisation. The membership information was provided by the organisation, after masking the members' names before they are handed over to the research student. Therefore, the members are not traceable from the information provided. In addition, sensitive information such as credit cards and payment instructions are not provided for this research project. The members (different from the participants) are the target 'customers' whom the not-for-profit organisation is aiming to analyse to provide effective contextual marketing of training courses. The member's dataset is only redacted secondary data sources which entail the same data fields that could be used for the application of data analytics techniques for the organisation.

1.8. Thesis Structure

This thesis is organised in the following sequence to facilitate readers' understanding:

Chapter one: Introduction outlines the trends of data analytics and identifies the research gaps. It also deals with the research questions, aims, objectives, methodology, and ethical considerations. The research rationale in this chapter discusses the contribution of this research to both the academic and professional body of knowledge.

Chapter Two: Literature review presents the backgrounds, historical developments, recent trends, and business impacts of data analytics strategies. Insights from research, challenges and lessons learnt from failure to implement data analytics strategies are shared. In addition, research gaps are identified, and illustrations are provided on how the research gaps lead to research questions, aims, and objectives.

Chapter Three: Research methodology discusses the research philosophy and the rationale behind the choice of research methodology adopted for this research project. The research methodology includes layers outlined in the research onion, such as approaches, strategies, choices, time horizon, techniques, and procedures, as proposed by Saunders et al. (2007). Ethical issues and measures taken to address the risks are also outlined in the chapter.

Chapter Four: Results and discussions provide the observations of the research work. The data collected through semi-structured interviews and archival records are analysed to answer the first research question. The research project assists the case study organisation to perform mapping to suitable training courses using members' profile information. Lessons learnt from the analyses are drawn and discussed in the chapter to answer the second/last research question.

Chapter Five: Conclusion, Limitations, and Future work reflect on the research journey, research limitations, and lessons learnt. Contributions to the body of knowledge are highlighted and recommendations for future research are also made.

1.9. Summary

As noted in various research works, there are opportunities for organisations to use data analytics to launch new business models and engage customers to gain competitive advantages. These opportunities are not confined to large commercial organisations, but also small, not-for-profit organisations. As most of the research works are done using large, commercial organisations, there is little research work using small organisations, who have limited resources and know-how. The research gaps highlighted the need for research work using small, not-for-profit organisations, who need assistance to launch data analytics strategies successfully.

This research work intends to use a small, not-for-profit organisation in Singapore as a case study. The lessons learnt from this project work are expected to benefit other similar organisations to introduce their respective data analytics strategies.

The research project starts by identifying the challenges and constraints to implement a data analytics strategy. This is then followed by helping the small, not-for-profit organisation devise appropriate plans to launch data analytics strategies successfully.

The entire research project will follow strictly the research methodology to ensure that the outcomes are evidence-based and objective. As the research student is also a volunteer in the organisation, he is considered an insider researcher. Ethics considerations, such as benefit and harm, informed consent, and confidentiality, were addressed as part of the research project.

Chapter 2. Literature Review

2.1. Preamble

This chapter starts with the management of literature review in section 2.2, and discussions of data analytics trends in section 2.3, followed by the introduction of commonly used terms, such as data analysis, data warehouse, data mining, and data science in section 2.4. The historical development of data analytics is discussed in section 2.5 before outlining the benefits attributable to organisations in section 2.6. Sections 2.7 to 2.12 cover the types of data analytics, challenges, and frameworks of implementing data analytics for organisations of all sizes. Research gaps, questions, aims and objectives are identified in section 2.13. Section 2.14 identifies the key frameworks that will guide this research project and section 2.15 provides the summary of the chapter.

2.2. Management of Literature Review

The literature searches are done using both electronic and paper-based approaches, focusing on sources from the 2000s onwards. The thematic approach is adopted by searching for keywords drawn from the research questions and aims. The searches targeted peer-reviewed journal articles, academic books, magazines published by reputable professional bodies, publications by government agencies, and companies' websites. Through the initial reviews, common themes on data analytics are drawn to generate new keywords that are used for further searches throughout the research project.

The primary keywords are illustrated in Figure 2.1 below.

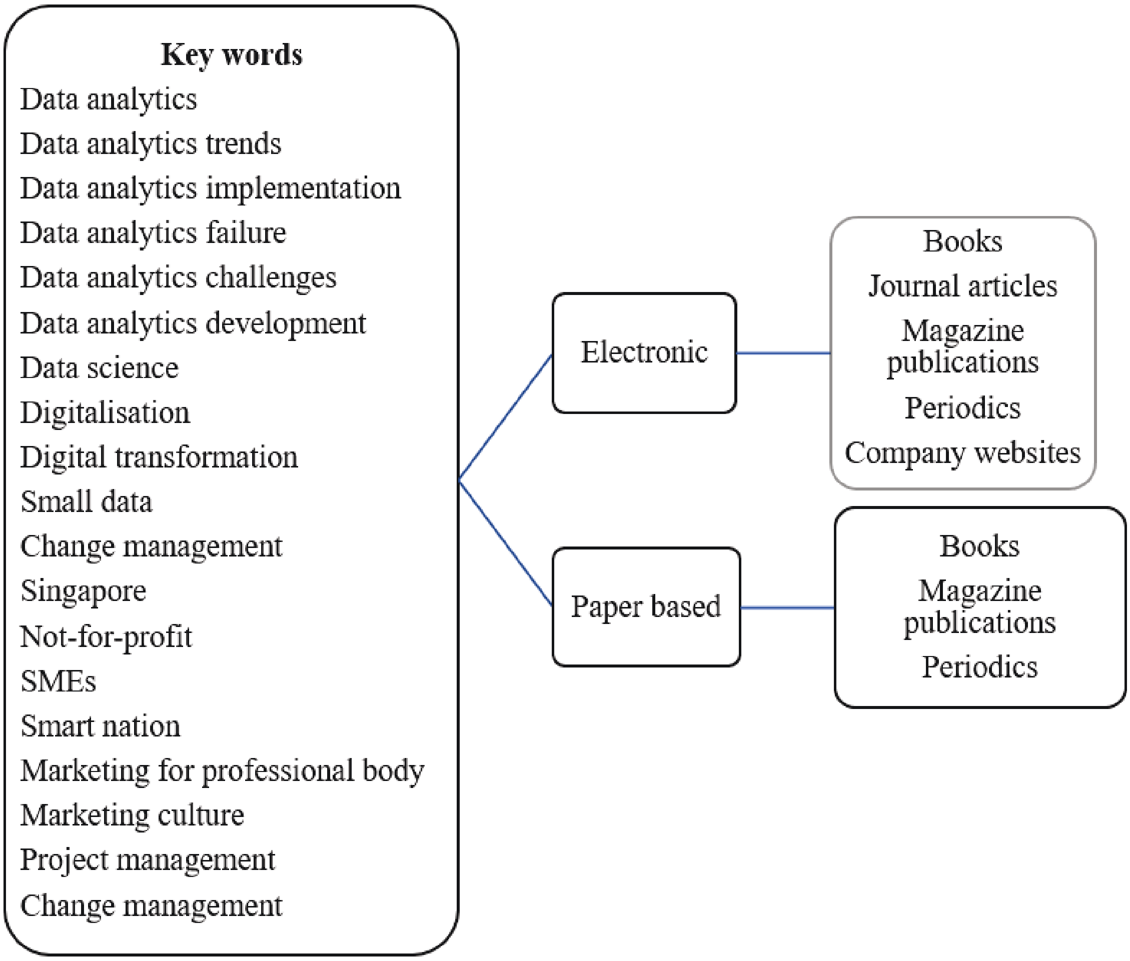


Figure 2.1: Literature review search strategy

2.3. Data Analytics Trends

Many organisations have used data analytics to create new business models, gain competitive advantage, and successfully disrupt conventional business models (Gartner, 2018; Hair et al., 2018; Provost and Fawcett, 2013). This is aided by the availability of data collected digitally, which has fuelled the investment in data analytics in every aspect of business, such as operations, marketing, manufacturing, customer behaviour, and supply-chain management (Marr, 2016; Provost and Fawcett, 2013). Data analytics strategies enable organisations to gain insights from the data to perform better-targeted marketing, cross-selling and online advertising (Provost and Fawcett, 2013), and it is affecting all industries and geographical areas (Gartner, 2018).

One of the examples was Uber, whose business model relied on data analytics (Marr, 2016). Uber, in essence, is a taxi booking company capable of linking passengers, who want to get from point A to point B, with drivers who are willing to take them from point A to point B. In addition to matching passengers to drivers, or vice versa, Uber uses both internal and external data, such as traffic conditions, the number of drivers available, and the number of passengers in demand, to calculate dynamic fares, which is also called "surge pricing" (Marr, 2016). The concept is similar to those used by hotels and airlines. When the demand is high, the prices would increase. On the other hand, the prices would decrease when the demand is low. Uber has developed an algorithm to adjust travel fares using real-time data. The dynamic fare system would encourage more drivers to drive during peak hours, hence increased the supply. However, when the demand is low, the prices would decrease, thus encouraging drivers to take a rest, therefore reduces the supply.

While Uber, which started in San Francisco in 2009 (Hartmans and Leskin, 2019; Marr, 2016), has been successful in using data analytics to create a new business model and disrupt traditional taxi companies, the competitions in the industry are extremely high. This is because other start-up companies, such as Lyft, Sidecar, and Haxi, are using a similar concept to vie for business, and Marr (2016) has warned that the ultimate winner is likely to be the one who can manage the best use of available data to improve their services and provide customers with the best.

Another company that has used data analytics to gain competitive advantages is Amazon, whose original business model was an online bookshop (Schneider, 2019; Marr, 2016). However, Amazon has outgrown that to become one of the largest retailers in the world. The success of Amazon is built on the foundation of understanding and predicting their customers' needs. Amazon started by collecting customers' data to form a "360 degrees view" of every customer (Marr, 2016).

For instance, when consumers browse its website, Amazon collects data such as the time they spent on each page, the language they used, the purchases they made, the shipping addresses, and the reviews they gave. In addition, if the consumers are using Global Positioning Systems (GPS) enabled smartphones or other devices, Amazon also collates their location data. With the information, Amazon can profile the consumers and map them to others with a similar profile. Thereafter, using the purchase history of people who shared similar profiles, Amazon uses a software engine to predict what the customer would like to buy and provide them with suitable recommendations. This saved the customers from searching for items in the catalogue. This technique of providing recommendations to customers and cross-selling products has contributed to one-third of Amazon's sales revenue (Lin, 2014; Wills, 2014).

The above trends are summarised well by Provost and Fawcett (2013) who stated that organisations are using data analytics to gain insights in all aspects of business, in particular, target marketing, consumer behaviour management, cross-selling and online advertisement. Chang (2021) advocated that digitalisation and data have provided new ideas and options for decisions and interactions between people and organisations.

2.4. Definitions of Similar Terms

The subject of data analytics has captured the wide attention of businesses as many start-up companies have successfully used it to create new business models and disrupt traditional businesses (Segarra et al., 2016). While attention is generated recently, the concept of data analytics is not new. Before we dwell further on the history of data analytics, let us examine the definitions of commonly used and similar terms, like data analysis, data warehouse, data mining, data science, and big data, that are closely related and could confuse.

2.4.1. Data Analytics

Larson (2018) defined data analytics as a field that extracts insights from various forms of data. Taking it one step further, data analytics is defined as using applied analytical techniques (such as statistical, quantitative, contextual, predictive, and cognitive models) to draw business insights from the data and they facilitate fact-based planning, learning, and decision making (Ransbotham et al., 2016; Wills, 2014). Similarly, Segarra et al., (2016) implied that data analytics is the use of technological capabilities to study customer data to provide businesses with insights about customer behaviours and trends.

Drawing from the above discussions, the key to data analytics is the ability to draw insights from data.

2.4.2. Data Analysis, Data Warehouse, and Data Mining

In defining data analytics, Sun et al (2017) started by looking at the definition of data analysis, which is defined as techniques of using tools to organise and study data to reach certain conclusions or to make predictions. The process may include examining and summarising data to conclude (Sun et al, 2017). Provost and Fawcett (2013) highlighted that data analytics include the evaluation of project feasibility by reviewing the assumptions and proposals systematically. In summary, data analytics do more than data analysis, because the former relies on communication or web technologies as well as evaluation (Sun et al., 2017; Provost and Fawcett 2013).

It can be argued that data analytics is the art, while data analysis is the science and technology, of examining, summarising, and drawing conclusions about data, to learn, describe and predict something. Knaflic (2015) further argued that using the data to tell stories is the most important stage to drive better decision-making, and this must be done by an analyst or communicator, not the machine.

The above explanation is contrasting to the views of Aasheim et al., (2015), who argued that data analysis and data analytics are used interchangeably but data analytics is the analysis when applied to large data set from big varieties. On the other hand, Segarra et al., (2016) highlighted that data analytics include various aspects, such as statistical techniques, data mining, and visualisation, amongst others. Statistical techniques identify correlation and causal relationships among the data while data mining is used to recognise patterns through machine learning and statistics (Segarra et al., 2016).

Based on the above discussions, data analytics is more than technical modelling, as it also encompasses visualisation, which is an important component to depict data into easily understood presentations, such as charts, tables, images, or diagrams, for communications (Segarra et al., 2016; Knaflic, 2015).

Segarra et al., (2016) and Sun et al (2017) claimed that data analytics include various aspects, such as data analysis, data warehouse, data mining, statistical modelling, and visualisation. Sun et al (2017) proposed to use the following framework to represent data analytics:

Data analytics = data analysis + data warehouse + data mining + statistical modelling + visualisation

Comparing the frameworks proposed by Segarra et al., (2016) and Sun et al (2017), the latter has added a data warehouse, which is used to describe a huge database for storage of data (Sun et al, 2017), to the data analytics framework.

2.4.3. Data Science

"Data science" is another term that is closely related to data analytics. Larson (2018) highlighted that data science focuses on all aspects such as collecting, modelling, analysing, and applying data through statistical methods. She argued that data analytics is a new form of competition, which uses statistics, quantitative analysis, and predictive techniques, based on data, to compete in traditional areas. Although the two terms (data science and data analytics) are used interchangeably, Larson (2018) implied that data science is the process involving the collection and manipulation of data to draw insights, whereas data analytics is the application of those insights to gain competitive advantages. This argument is supported by Provost and Fawcett (2013).

In addition, Larson (2018) noted that data science is different from data mining. Firstly, data scientists are expected to produce results in a matter of days whereas data mining may take months. Secondly, data science involves a wider spectrum, such as merging data for analysis and the use of visual aids to communicate insights.

In a study to ascertain the similarities and distinctions between data science and data analytics, Aasheim et al., (2015) compared the course content of various universities in the USA. They found similarities between the two as both courses included mathematics, statistics, data mining, data visualisation as well as modelling techniques, and analytics techniques. However, data science courses have more emphasis on the specialisation of mathematics, such as linear algebra and calculus, as well as the implementation of tools and techniques. In contrast, data analytics courses focus more on the evaluation of tools and techniques. For data mining, data analytics put emphasis on the application, but data science courses emphasise algorithms for data mining. Lastly, while both courses cover data visualisation, data analytics courses stress that visualisation is a mean of effective communication, however, data science courses merely highlighted the types and techniques of visualisation.

By looking at the differences in the course content, the discipline of data science seemed to play the role of executing the techniques to analyse data while data analytics played the role of the applications. This is somewhat aligned with the definition put forth by Larson (2018). Similarly, Sonka (2016) referred to data science as extractions of knowledge from data.

2.4.4. Big Data

As the world was going through the digitalisation era, information was being captured and collected far more than ever before (LaValle et al., 2011) and this was happening at unprecedented volume (Lemieux et al., 2014). Coupled with emerging technologies, including big data analytics, the available data has made fundamental changes to businesses (Sun et al., 2017).

As there is no agreed definition for big data (Lin, 2014), a commonly used definition for big data included three dimensions, as they are known to be huge in "volume", high in "velocity" and big in "variety" (Yeo and Carter, 2017; Coleman, 2016; Campbell et al., 2015; Lemieux et al, 2014; Lin, 2014; McAfee and Brynjolfsson, 2012). The key differences between traditional transaction data and big data are volume, velocity, and variety (Larson and Chang, 2018). These three dimensions were commonly referred to as the three Vs. Volume referred to the amount of data that was beyond the storage capacity of commonly used technology infrastructure. Velocity referred to the speed where data was created or changed, while variety referred to the range of data types (e.g., structured and unstructured) and sources.

Instead of three Vs, Chang (2020) highlighted that there are four Vs, namely velocity, variety, veracity, and value, while Cheng et al., (2015) argued that there are five Vs, which include volume, velocity, variety, veracity, and value. Veracity refers to the inconsistency and incompleteness of data, while value refers to benefits and insights to the businesses.

A different version was put forth by Sun et al (2017), who adopted the three Vs (volume, velocity, and variety) but added that big data should also include mobility and detail. They claimed that mobile devices, such as smartphones, were creating data on the move (mobility), data are being changed in greater facets (detail).

Marr (2016) highlighted that data is being created in various channels, such as emails, WhatsApp, Twitter, Facebook, Youtube, and Internet of Things (IoT). In the past, data with big volumes would put pressure on the storage device. However, the advancement of technologies, such as Hadoop, enables organisations to store data in different databases in different locations, with the servers or databases being connected via networks to enable analysis to be performed concurrently (Marr, 2016).

Advanced algorithms are emerging daily to help organisations strengthen their data analytics capabilities using big data (Marr, 2016; Provost and Fawcett, 2013). For example, database querying, such as Structured Query Language (SQL) and On-line Analytical Processing (OLAP) are designed to help analysts or end-users explore the data, and find the answer based on their needs (Provost and Fawcett, 2013). Other techniques, such as artificial intelligence, machine learning, and applied statistics are advanced technologies, which are too complex for small enterprises with limited resources, hence are not discussed in this project.

2.5. Historical Development of Data Analytics

With the understanding of the commonly used terms, such as data analytics, data analysis, data warehouse, data mining, and big data, which are closely related, it is time to explore the history of data analytics.

Big data analytics has been made feasible lately because of the advancement in technology and computing power (Davenport, 2014). However, data analytics is not only confined to big data analytics, but should also be relevant to small, medium-sized enterprises (OECD, 2018; OECD, 2017; OECD, 2000). Supporting the view is Wills (2014), who argued that there are three main forms of data analytics, namely real-time analytics, predictive modelling, and small data analytics.

The foundation of data analytics was laid in 1970, where "decision support" made use of data analysis to support the decision-making process (Davenport, 2014). This was developed into "executive support" in 1980, where data analysis was used for decisions by senior executives. In 1990, "online analytical processing" or OLAP, was software developed to analyse multidimensional data tables. Big data emerged in 2003 when high technology firms, such as Google and Yahoo, used them for analytics to understand customer behaviours (Larson and Chang, 2018), and the analytics capability was developed to include very large, fast-moving, and unstructured data (Davenport, 2014).

2.6. Benefits of data analytics

Data-driven organisations performed better, in terms of productivity and profitability than their rivals (Ang, 2021; McAfee and Brynjolfsson, 2012) because organisations that used data can make better decisions to gain a competitive edge over their competitors who are not data-driven (Capriotti, 2014).

Insights drawn from data analytics can help organisations to understand customers' behaviours and identify needs that are not met by current business products and services (Segarra et al., 2016). Therefore, the insights can be deployed to generate ideas for new products and services that better meet customers' needs. These new products or services can be delivered to customers using new business models that better suit the customers (Ang, 2021). A classic example is Uber (Marr, 2016), which used data analytics and applications to change the way taxi companies worked. In doing so, Uber has enhanced customer satisfaction. Yeo and Carter (2017) indicated the same as they said that data analytics offered tremendous opportunities for organisations to use the insights from data analytics to create new business models.

Lin (2014) was a supporter of data analytics, as he claimed that big data can provide insight and create competitive advantages for businesses. This is supported by Gartner (2018) who warned that digital disruption is impacting all industries and geographies. In addition, digital disruption is not only impacting technology, but also customer experience, behaviours, and data (Gartner, 2018). The benefits of data analytics include enabling organisations to provide personalised marketing, reaching out to new customers, improving operational efficiency, enhancing processes, strengthening risk management techniques, and building up fraud detection capability (Ang, 2021; Lin, 2014). Data analytics can be extended for usage in agriculture to increase farm production (Lin, 2014).

To support his arguments, Lin (2014) provided examples, such as Amazon has increased its sales revenue by using data analytics to group customers with similar behaviours and used historical data to understand the purchase patterns of each class of customers. By doing so, Amazon provided personalised recommendations to the customers by predicting their desires (Marr, 2016), which contributed to one-third of the revenue in Amazon (Lin, 2014).

In another example provided by Lin (2014) Aviva collected lifestyle data of its customers and use data analytics to identify new customers who have lower risks of illness. Using the results of the data analytics, Aviva was able to waive the lab tests for new customers with low risk of illness when they purchased health insurance, thereby saving the costs incurred for lab tests.

Similarly, to save costs, UPS monitored individual parts on trucks to schedule replacements on a "need to" basis instead of replacing the parts after a fixed duration. As a result, UPS was able to save millions of dollars every year (Lin, 2014).

Using a different method, MasterCard, which processed credit card transactions, was able to analyse the transaction data to identify customers' purchase patterns (Lin, 2014). For example, data demonstrate that after filling the petrol at 4 pm, customers were likely to make grocery purchases. With this insight, MasterCard sold the information to supermarkets, which then promoted marketing schemes to the customers to entice them to make purchases at the supermarkets. By doing so, MasterCard was able to generate additional revenue.

The above examples reveal that there are numerous ways to use data analytics to gain insights, which are obtained mainly from market analysis, customer segmentation, and personalisation (Rehman et al, 2016). The insights enable organisations to gain competitive advantages. However, Ransbotham et al., (2016) have warned that the extent of the competitive advantages is diminishing, because more organisations are doing the same.

2.7. Types of data analytics

After reviewing the benefits and opportunities of adopting data analytics strategies, it is time to proceed to explore the types of data analytics, for a better understanding of how data analytics can be used to generate competitive advantages.

Fadairo et al., (2015) claimed that there are two forms of data analytics, namely, descriptive analytics and predictive analytics. Examples of descriptive analytics include standard reporting, dashboards, drill-downs, and clustering, whereas predictive analytics include modelling, simulation, and text mining.

Going further, Capriotti (2014) suggested four categories of data analytics, as he also proposed diagnostic and predictive types of data analytics, on top of the descriptive and predictive data analytics proposed by Fadairo et al., (2015). Descriptive data analytics help organisations understand what has happened, diagnostic data analytics provide assessment on why certain events have happened, predictive data analytics forecast what will most likely going to happen, and finally, prescriptive data analytics proposed options for organisations (Capriotti, 2014).

Using different perspectives, Wills (2014) maintained that real-time, predictive modelling, and small data are three forms of data analytics. Real-time analytics analyse data immediately after it becomes available to provide instant and actionable information. As this form of analytics studies data continuously, it is the most advanced form of data analytics (Wills, 2014). Predictive modelling data analytics use models and algorithms to analyse data, find related patterns, and predict outcomes, while small data analytics perform analysis over a small population of data. Wills (2014) revealed that small data analytics does not add undue financial burden to organisations, as it does not require a huge investment in technologies and training.

Adopting a different prism, Lin (2014) categorised the types of data analytics using the project goals and characteristics, as he reported that data analytics could be (i) operational analytics; (ii) operational processing analytics; (iii) relationship and behavioural analyses; and (iv) social brand/sentiment analyses. In terms of popularity, Lin (2014) reported that operational analytics, such as fraud analyses, customer relationship management, and risk assessment, is the most common type of analytics. The popularity is followed by operational processing analytics, like customer care, billing, and rating. Relationship and behavioural analyses are the third most popular type of analytics, which involved clustering, customer churn analysis and grouping, and relationship analysis. Examples of the fourth type of analytics, social brand/sentiment analyses, are sentiment analysis and opinion mining.

Provost and Fawcett (2013) mentioned that techniques used to mine data for insights can be categorised into three broad ways, namely classification, regression, and clustering. Classification involves assigning individuals into similar groups and using scoring systems to predict their likely responses to certain stimuli. Regression goes one step further by attempting to predict the extent of the response to the stimulus. Clustering is useful to explore whether there are similar groups within the population as it attempts to group individuals without a specific purpose. Provost and Fawcett (2013) also introduced other techniques, such as database querying, machine learning, and artificial intelligence.

2.8. Challenges to implementing data analytics

While data analytics offer huge opportunities, implementing the strategies presents equally huge challenges to management (McAfee and Brynjolfsson, 2012). The challenges are multi-facets, as they are not confined to technical aspects but also organisation aspects, such as leadership, talent management, decision-making protocols, and culture. The organisation aspects are more critical because "culture trumps data", therefore, organisations cannot successfully implement data analytics strategies if they do not understand the culture (Ransbotham et al., 2016).

The sections below discuss challenges in greater detail.

2.8.1. Technical – data management

Technologies have advanced, and with the availability of open-source applications such as Hadoop, the costs of analytics have reduced while their capabilities have improved to serve greater needs of data analytics (Segarra et al., 2016; McAfee and Brynjolfsson, 2012). On the other hand, organisations are struggling to handle data to ensure that data quality is maintained (Ransbotham et al., 2016; Cheng et al., 2015). The challenges are particularly acute for big data.

A review of the practices in the banking sector confirmed the challenges relating to data management argued by Cheng et al., (2015) and Ransbotham et al., (2016). After the global financial crisis in 2018 – 2019, the Basel Committee on Banking Supervision (BCBS) highlighted that many banks did not have risk data readily available to aggregate their positions for quick and accurate risk management. BCBS listed the lack of risk data as one of the most significant lessons learnt from the crisis (BCBS, 2013). As a result, BCBS issued a set of principles on risk data for banks to follow to provide accurate, comprehensive, and timely risk reports. Despite giving the world's biggest 31 banks a timeframe of three years to comply with the principles, by 2016, only three (approximately 10%) of the global top banks were assessed to have fully complied with the principles to ensure integrity and accuracy of risk data (BCBS, 2018).

The above demonstrates that ensuring the availability of accurate data is a big challenge among organisations, including leading global financial institutions, which have invested more vastly in technologies.

The Enterprise Data Management (EDM) Council reinforced the observations made by BCBS. They highlighted that managing data for consistent definitions and records are huge challenges to many organisations, especially those who have gone through acquisition exercises (EDM Council, 2018). They emphasised that managing data laid the foundation for reliable data analytics. Therefore, without proper data management, there would be no reliable data for meaningful data analytics.

The good news is, with advancement in technologies and competitions, the costs of implementing infrastructure that support data analytics strategies are decreasing (Segarra et al., 2016).

2.8.2. Organisation – leadership

As the successful implementation of data analytics strategies does not depend solely on the amount and quality of data, leaders must believe in the strategies to provide clear visions, objectives, and directions (Ransbotham et al., 2016; McAfee and Brynjolfsson, 2012).

The lack of top management's priorities and unclear strategies to apply data analytics are causes for failures to implement data analytics strategies (Ransbotham et al., 2016). Senior management needs to devote time to understand the implications of digital revolution, actively engage in analysing and monetising data, as well as attract and retain talent in the data domain (Gartner, 2018), and they need to ask the right questions to guide the organisations towards success (McAfee and Brynjolfsson, 2012).

2.8.3. Organisation – talent management

As new types of data, especially unstructured data, are created and collected, data handling requires new techniques, which are rarely taught in schools (McAfee and Brynjolfsson, 2012). Therefore, the rapid advancement of technology has put pressure on staff to keep pace with the evolving technologies, giving rise to talent shortages (Ransbotham et al., 2016; Segarra et al., 2016; Fadairo and Maggio, 2015; McAfee and Brynjolfsson, 2012). As a result, the cost pressure is compounded by the increasing hiring costs for talents with the right skills (Fadairo and Maggio, 2015).

2.8.4. Organisation – decision-making protocols and culture

According to the traditions of most organisations, the decision-making process largely relied on the "highest-paid person's opinion" (McAfee and Brynjolfsson, 2012) or senior managers (Ransbotham et al, 2016). The traditional method of making decisions based on intuition worked when data was not readily available and was expensive to obtain (McAfee and Brynjolfsson, 2012).

However, with the availability of data in the current digital world, decision-making processes that relied on data are better than those relied on intuition (Ransbotham et al., 2016; McAfee and Brynjolfsson, 2012). The senior members must lead by example to relinquish their pride by giving up intuition-led decision-making processes, especially when the data showed a picture that differs from their intuitions (Ransbotham et al., 2016; McAfee and Brynjolfsson, 2012). This requires a change in mindset at the senior level (Smith, 2017).

2.9. Frameworks to Implement Data Analytics Strategies

As discussed above, organisations must understand the organisation aspects, such as culture, for the successful implementation of data analytics strategies (Ransbotham et al., 2016; McAfee and Brynjolfsson, 2012). Employees' resistance to change is reported as the key challenge to implementing a data analytics strategy (Wills, 2014). As such, employees must be shown the value of data analytics to allow them to appreciate the drivers and values of changes, thereby reducing the resistance. This can be achieved by "start small". For example, organisations can pilot the strategies with teams that are less than five persons as an experiment before scaling up the capabilities (Bump, 2015).

Through piloting, organisations can avoid making a huge investment at the start and they can follow a four steps strategy by experimentation, measurement, sharing, and replication (McAfee and Brynjolfsson, 2012).

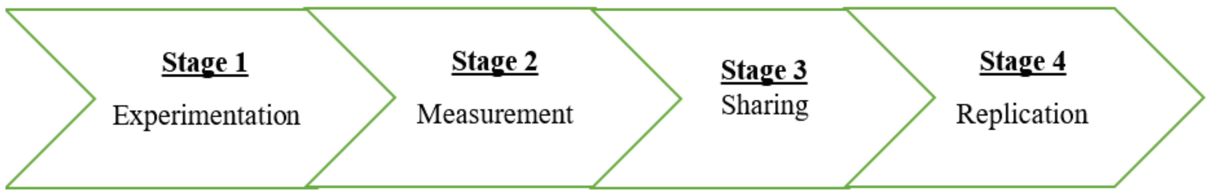


Figure 2.2: McAfee and Brynjolfsson (2012) Four Stages Framework

A similar approach was put forth by Bump (2015), who suggested a three-stage framework. The first stage was to kick off with a pilot in a test environment. With the success and experience of the pilot, organisations can proceed to the second stage where a data analytics engine would be developed, and organisations could invest in training more employees to get them onboard the data analytics project. After success in stage two, organisations could move to the final stage where data analytics would be expanded for deployment across all departments. In the final stage, organisations would train more employees and could consider incorporating predictive and visualisation forms of data analytics.

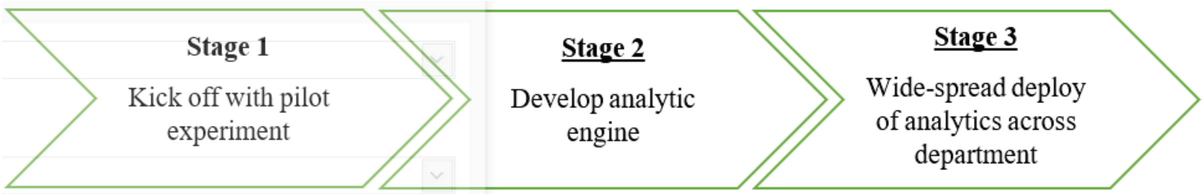


Figure 2.3: Bump (2015) Three-Stage Framework

While the above frameworks facilitate the implementation of data analytics strategies, the data analytics strategies must be aligned to the overall organisation objectives (Segarra et al., 2016).

The above discussions have included the term “framework”, which is frequently used interchangeably with the term “model”, as it is unclear that they are the same (Soni and Kodali, 2013). Broadly, “framework” describes “how-to” whereas the “model describes the “what” (Soni and Kodali, 2013; Yusof and Aspinwall, 2000).

It is argued that “framework” is an overarching concept that includes guidelines, models, and taxonomies (Mazalek and Hoven, 2009). It is used as a guiding torch to help organisations implement new philosophies. As such, a framework should provide the sequence of actions and described the structural relationships and connectivity of various elements (Soni and Kodali, 2013)

On the other hand, “Model” is an abstract exemplar that describes the functioning of systems (Mazalek and Hoven, 2009), and not all of them are executable (Mello et al., 2003)

In this research project, “framework” is used to describe guidance when “how-to”, e.g., steps or executable stages are provided. On the other hand, “model” is used to describe guidance when “what” is provided and may not be necessary executable.

2.10. Data Analytics for Small, Not-for-profit Organisations in Singapore

Through literature review, it is noted that most of the research works were performed for commercial organisations in the developed countries, such as Europe and the USA. There were little researches for organisations in Singapore, especially for small organisations.

2.10.1. Singapore and Her Smart Nation Initiatives

Singapore is a small country in Southeast Asia, and she was granted self-governance by the British government in 1959 and full independence in 1965. When the country gained independence, she has no natural resources, and the workforce consisted mainly of uneducated and unskilled workers. Few people were optimistic that Singapore would survive when it got independence, however, against all odds, she did not only survive but her per capital gross domestic products (GDP) grew from US$400 in 1959 to US$22,000 in 1999 (Lee, 2000). Her GDP per capita grew further to US$64,000 at the end of 2018 (DOS, 2018).

Singapore has a stable government that executes policies consistently to build an excellent reputation that garners confidence from the international fund managers, investors, and organisations (Lee, 2000). Small medium-sized enterprises (SMEs) in Singapore contributed nearly half of the GDP (Microsoft and ASME, 2018) and employed about two-third of the Singapore workforce (Microsoft and ASME, 2018; Teo, 2013).

The Singapore government, being proactive and pro-business, has encouraged the entire population to embrace digital transformation through its “smart nation” initiatives. As noted in a speech by the Prime Minister, the Singapore government wanted the entire nation to use technology extensively and systematically as a coherent whole. In doing so, the government believed that it would improve the lives of its population by creating jobs as well as engaging communities (Lee, 2014).

As the population is aging rapidly, Singapore cannot rely on an increase in the number of working hours, but rely on productivity for growth (Subhani, 2020). The borderless digital economy is expected to plug Singapore into the global space to create new business opportunities, which can benefit particularly SMEs (Hussain, 2020).

Despite the encouragement by the government to embrace digitalisation, studies revealed that a substantial proportion of the SMEs in Singapore have not adopted data analytics (Ang, 2021; Ramchandani, 2017), with approximately half (43%) of them have not heard about the term "digital transformation" (Microsoft and ASME, 2018), and the majority (85%) of the workers in Singapore are not confident with data analytics (Shivkumar, 2019). The awareness level among the owners or key decision-makers in small enterprises was much lower, compared to their counterparts in medium and large corporations (Microsoft and ASME, 2018).

These are worrying trends, given that the SMEs in Singapore contributed nearly half of the gross domestic product (GDP) (Microsoft and ASME, 2018) and employed about two-third of the Singapore workforce (Microsoft and ASME, 2018; Teo, 2013). As the owners are not aware of data analytics, they are unlikely to train their workers to be equipped with new skills.

These findings suggest that more education efforts are needed to raise the awareness of SMEs owners and decision-makers about the benefits of digitalisation and data analytics. A higher awareness level would encourage more owners and decision-makers in SMEs to pursue digital and data analytics strategies.

However, there are some bright spots as Microsoft and ASME (2018) revealed that SMEs who actively implement digital strategies, are expecting 26% in revenue growth and 22% in cost-saving. Realities prove that organisations that embrace digital transformation generate higher revenue and profit (Ang, 2021; DBS, 2019). Organisations with a higher score in "corporate data literacy" also scored better in enterprise value, productivity, and gross margin (Shivkumar, 2019). With a well-maintained infrastructure and skilled workforce to support digitalisation (Choo, 2020), Singapore SMEs have a good platform to embark on digital transformation and data analytics.

2.10.2. Small and Medium-Sized Enterprises (SMEs)

The Organisation for Economic Co-operation and Development (OECD) noted that there was no universally accepted definition for SMEs (OECD, 2017). In the USA, SMEs are organisations with less than 500 employees (OECD, 2017). In contrast, SMEs are defined by OECD as organisations that employed less than 250 employees (OECD, 2017; OECD, 2000), which is also the most commonly used definition (OECD, 2000). In Singapore, SMEs are defined as organisations with less than 200 employees and less than SGD 100 million turnovers (Enterprise Singapore, 2019; Teo, 2013).

2.10.3. Not-for-profit Organisations

Not-for-profit organisations are economic entities whose purposes and objectives are not to make a profit (Henke, 1972). They usually have no equity shares, and they include religious organisations, universities, voluntary agencies, and charitable organisations, social services, associations, clubs, and unions (Newman and Wallender, 1978; Henke, 1972) as well as professional bodies (Hess et al., 2019).

While making a profit is not the objective, not-for-profit organisations need to be sustainable through proper capitalisation and funding (Anderson, 2008). This is because not-for-profit organisations are consuming increasing proportion of national resources and they are influencing more people (Newman and Wallender, 1978).

In the changing landscape where technology is fuelling the emergency of new business models, not-for-profit organisations are not spared the need to change. For example, professionals, especially the younger ones, expect professional organisations to engage members on a personalised basis using customised communication strategies, and those who do not would become obsolete soon (Moore, 2019). Despite being important and being affected, the impacts of technologies on not-for-profit organisations are often overlooked (Eusanio and Rosenbaum, 2019).

With the changing landscape, not-for-profit organisations must transform the data they have collected into valuable information and insights to improve their operations and achieve their missions (Eusanio and Rosenbaum, 2019). Professional bodies, which are not-for-profit organisations (Hess et al., 2019), can use data to make evidence-based decisions to set realistic goals and formulate practical strategies (Moore, 2019).

As not-for-profit organisations differ widely from commercial organisations, the change strategies must be modified to accommodate the constraints of not-for-profit organisations (Newman and Wallender, 1978). This is because technologies that work for commercial organisations may not work the same way for not-for-profit organisations (Kilbourne and Marshall, 2005). As this is an area that is often overlooked (Eusanio and Rosenbaum, 2019), further research works are necessary.

2.11. Challenges Confronting SMEs

As discussed previously, the take-up rate of data analytics is slow among small organisations, including not-for-profit organisations. The slow adoption rate for data analytics is not unique to Singapore SMEs. Coleman (2016) highlighted the same observation, where SMEs in the United Kingdom (UK) were relatively slow to adopt data-focused strategies. Similarly in OECD countries, SMEs are lagging their bigger counterparts in the adoption of data analytic strategies (OECD, 2018; OECD, 2017; OECD, 2000).

The OECD had devoted at least two ministerial conferences to discuss the trend and urged various sectors, including the governments, to help the SMEs by lowering barriers to adopting data analytics. Likewise, Ogbuokiri et al., (2015) who performed a study on data analytics among SMEs in Africa, argued that SMEs can benefit from data analytics. Data analytics can benefit big and small organisations, for-profit as well as not-for-profit organisations (Hair et al., 2018; Kitchin and Lauriault, 2015).

Below are some of the challenges confronting SMEs and the causes for the slow data analytics adoption rates among SMEs.

<u>Organisational Challenges - Leaderships</u>

Reasons for the slow adoption of data analytics could be attributed to the lack of awareness. Firstly, the SME owners or key decision-makers are not aware of the benefits that digital transformation can bring to the organisations (Microsoft and ASME, 2018). Secondly, the lack of awareness about data analytic strategies has led to wrong perceptions, such as perceived high costs (Microsoft and ASME, 2018; Ogbuokiri et al., 2015) and that data analytic strategies are too complex for SMEs (Microsoft and ASME, 2018; Ogbuokiri et al., 2015). Many SMEs wrongly believed that data analytics solutions are designed for large organisations but not for SMEs (Ogbuokiri et al., 2015).

<u>Organisational Challenges – Talent Shortages</u>

Some other causes for the slow adoption of data analytics among SMEs are high upfront investment (OECD, 2018; OECD, 2017), lack of knowledge (OECD, 2018; OECD, 2017), lack of IT skills (Gartner, 2018; Microsoft and ASME, 2018; Coleman, 2016), lack of statistical skills (Coleman, 2016), weak managerial skills and human capital (Chong and Nippani, 2021; Shivkumar, 2019; OECD, 2018; OECD, 2017) and lack of an in-house innovation process (OECD, 2017). These can be summed up as talent management challenges, and they are not confined to SMEs. As resources like data scientists are limited in the market, organisations must attract, train, and retain talented people in the digital domains (Chong and Nippani, 2021; Gartner, 2018).

Specific to Singapore SMEs, one fundamental issue could be complacent, as Microsoft and ASME (2018) suggested that there is a lack of urgency to explore data analytics, which in turn led to the lack of interest to explore data analytics. Therefore, the awareness level remained low, and the take-up rate is slow.

<u>Organisational Challenges - Culture</u>

The soft part of the organisations cannot be overlooked as employee resistance and organisation culture could de-rail new strategy adoptions (Microsoft and ASME, 2018), as successful implementations of data analytic strategies require widespread culture change (Shivkumar, 2019). The culture change can be made in stages, through training and involving employees in decision making to facilitate their understanding and buy-in, which could not be achieved in a short time (Shivkumar, 2019).

While in general, SMEs are slower in taking up digitalisation and data analytics (Ang, 2021; OECD, 2017), there were some SMEs who were extremely innovative in using data analytics to gain competitive advantages. Therefore, it is important not to view all SMEs in the same light.

2.11.1. Promoting Data Analytics to SMEs

In Singapore, its ministers have been encouraging its population, including SMEs, to embrace the changes to reap opportunities created by digital transformation and data analytics (Lung, 2018), the ministers highlighted that data analytics can be used to create new economic resources for the country to gain competitive advantage and create a new engine for growth (Ong-Webb and Ang, 2017; Tan, 2016). The Trade and Industrial Minister also warned that Singapore companies must embrace digital transformation, or they will lose competitive advantages (Lai, 2020). It is noted that SMEs can adopt digital tools to increase the organisations' value and productivity by an average of 25% and 16%

respectively (Enterprise Singapore, 2020). The Prime Minister advocated that Singapore should be a place where data can be shared to encourage innovation and unlock value (Loh, 2018).

The government is leading the way by launching Digital Government Blueprint where all the civil servants will be trained in data skills within a decade (Loh, 2018). It has also launched a S$20 million fund to help Singapore firms to defray the costs of digitalisation (Ng, 2020).

Despite the encouragement by the government to embrace digitalisation, SMEs in Singapore are slow to adopt digitalisation strategies or data analytics (Ang, 2021; Shivkumar, 2019; Microsoft and ASME, 2018; Ramchandani, 2017).

The slow pace of adopting data analytics by the Singapore SMEs is alarming, as they ran the risk of losing out in the highly competitive world and being left behind (DBS, 2018; OECD, 2017). With technological changes, companies are operating more efficiently by digitalising their processes (Ang, 2021; Alibaba Cloud, 2018). those who do not digitalise will become less competitive. In addition, customers are becoming more demanding as they are expecting personalised services that are driven by insights (Alibaba Cloud, 2018). Therefore, those without digitalisation strategies and insights from data analytics will find it tough to satisfy customers' raising expectations.

The coronavirus disease (COVID) pandemic has changed the world, some traditional growth engines, such as international tourism and physical retail, will not be able to provide for economic growth in the near future, instead digital economy is expected to fill the gaps post-COVID (Skilling, 2021). Therefore, organisations, including SMEs, cannot expect to return to business as usual (Lai, 2020). The pandemic has accelerated technology adoption and digital transformation (Subhani, 2020), the Singapore Communications and Information Minister stressed that the pandemic has made it even more important for businesses to innovate and digitalise (Tan, 2020). As the digital economy has no border, the Minister emphasised that Singapore businesses, especially SMEs, must plug into the global digital space to fully reap the benefits (Hussain, 2020; Subhani, 2020).

SMEs are left with little choice but to embrace digitalisation and data analytics. As the global economies are becoming more integrated and interconnected, the opportunity costs for not embracing digitalisation and data analytics would become higher (OECD, 2018) and should be considered (OECD, 2017).

The Singapore government recognised that SMEs need help to achieve digitalisation and it has increased the support towards SMEs through the Grow Digital initiative (Tan, 2020). It has also provided a new toolkit to help not-for-profit organisations to embrace digitalisation for their corporate and administrative functions (Lim, 2020).

DBS (2019) advocated using digital technologies can provide the competitive edge that SMEs need. To be more specific, DBS (2018) urged SMEs to gain competitive advantages by incorporating data analytics into their corporate strategies. Similarly, Shivkumar (2019) advocated all companies, including SMEs in Singapore, embrace data analytics to succeed in the Fourth Industrial Revolution. The Singapore Ministry of Trade and Industry found that the adoption of digitalisation leads to an increase in value-add by 25% and productivity by 16% (Enterprise Singapore, 2020).

Data analytics can equip SMEs to gain competitive advantages in many ways, some of the examples are understanding their customers and their buying behaviours to provide customised services or products to the customers (DBS, 2019; DBS, 2018; Alibaba Cloud, 2018; Coleman, 2016), predict customers' needs (Pan and Sun, 2018), make better decisions (Pan and Sun, 2018), create new business opportunities (Microsoft and ASME, 2018; Ogbuokiri et al., 2015), prioritise areas for business expansion (Coleman, 2016), grow revenue (Pan and Sun, 2018; Microsoft and ASME, 2018) and improve productivity or reduce costs (Pan and Sun, 2018; Microsoft and ASME, 2018; Alibaba Cloud, 2018).

In terms of the organisations' value chain, data analytics can strengthen SMEs in Planning and Finance (Alibaba Cloud, 2018; DBS, 2018), Human Resource and employee deployment (Alibaba Cloud, 2018; DBS, 2019), Marketing (Alibaba Cloud, 2018; DBS, 2018), Sales (Alibaba Cloud, 2018; DBS, 2018), Logistics and Supply Chain (Alibaba Cloud, 2018; DBS, 2018), customer analysis (DBS, 2018).

In a study performed for the global economy, OECD (2017) highlighted similar advantages as the above studies. For example, data analytics can assist SMEs to gain competitive advantages to reach a greater scale and across borders while lowering costs (OECD, 2017). Therefore, SMEs are encouraged to use data analytics to respond quicker than their counterparts. This is an important capability that SMEs should develop to disrupt the strategies of their competitors as product life cycles are being shortened (DBS, 2018; OECD, 2017). Alibaba Cloud (2018) highlighted that digital transformation means business transformation. SMEs could play a more important role in the world's economy by generating employment opportunities and contributing to innovation if they successfully embrace and launch digital transformation and data analytics (OECD, 2017).

2.11.2. Options and Strategies to Adopt Data Analytics

SMEs are perceiving data analytics as extremely costly and complex projects for adoption (Ang, 2021; Microsoft and ASME, 2018; Ogbuokiri et al., 2015), therefore, there is a need for education to change the mindset of the owners and management members of SMEs.

Instead of putting data transformation as one big, lumpy and complex project, SMEs are advised to break the project elements into manageable chunks for analysis and prioritisation (Alibaba Cloud, 2018; DBS, 2014). It is recommended that SMEs give priority to data analytics or digitalisation to departments who could benefit most from the initiatives in the shortest timeframe, to achieve momentum. Alibaba Cloud (2018) put forth four-step strategies – plan, assess, adopt and optimise - for SMEs to digitise their business operations. This is similar to the three-stage framework proposed by Bump (2015), who encouraged that organisations start with a pilot project to test the environment before moving it to a bigger scale.

Figure 2.4: Alibaba Cloud (2018) Four Steps Framework for SMEs

Digital transformation is tantamount to business transformation; therefore, data analytics strategies must be supported by the top management to mobilise people across different functions to be aligned (Alibaba Cloud, 2018). This is because the transformation could impact the entire value chain for SMEs, ranging from product design to marketing, and logistics to Finance and Human Resource.

After obtaining top management support, SMEs must assess, identify, and articulate the problems that they want to solve using data analytics before they embark on the planning stage for the change (Alibaba Cloud, 2018). Depending on the types of problems that SMEs want to solve with data analytics, the tools and data required will differ. For example, if the objective of the data analytics project is to analyse data to achieve an understanding of business at one glance, business intelligence tools such as Tableau and Power BI can be deployed to build a dashboard for business indicator monitoring (DBS, 2018).

The architecture of data analytics should include four stages, namely, data generation, data storage, data analysis and processing, and data visualisation (Boulaaba and Faiz, 2018). In analysis and processing, Boulaaba and Faiz (2018) commented that data analytics can be categorised broadly into classification, clustering, prediction, mining for associated rules, generation, and trend detection. They further argued that the tools to be deployed should depend on the rules or the types of information to be extracted. For instance, Markov Random Field (MRF) framework can be used for classification type of analytics, Spatial Autoregressive (SAR) framework can be used for prediction type of analytics, Gaussian Processing Learning and Mixture framework can be used for trend detection type of analytics

Figure 2.5: Bouaaba and Faiz (2018) Platform architecture of data analytics

Provost and Fawcett (2013) have proposed other data analytics techniques for classification, regression, and clustering of data to gain insights. As “classification” involves assigning individuals into similar groups and using a scoring system to predict their likely responses to certain stimuli, it is a technique that can be explored for targeted marketing. Programs such as MapReduce are examples of tools or programs that can perform classification for targeted marketing. Regression goes one step further by attempting to predict the extent of the response to the stimulus. Clustering is useful to explore whether there are similar groups within the population as it attempts to group individuals without a specific purpose.

After idntifying the problems to be solved by data analytics, SMEs can proceed to select the data attributes required for the data analytics (Provost and Fawcett, 2013), and then plan for the change (Alibaba Cloud, 2018).

2.12. Change Management

As data analytics is relatively new for small, not-for-profit organisations, the implementation of data analytics strategies, which involves change in mindset and culture (Smith, 2017; Ransbotham et al., 2016; McAfee and Brynjolfsson, 2012), is akin to "change management".

Andersen (2012) argued that projects must start with a clear purpose, and it is the responsibility of the project owner to define the purpose, not the project manager. In addition, he highlighted that the project owner must establish metrics to measure the success of the project, communicate the strategic value to impacted parties, empower the project manager, and set expectations to measure the performance of the project manager. Similarly, Muller and Turner (2010) advocated that the project vision must be communicated by the project owner or sponsor. However, in contrast to Andersen (2012), Muller and Turner (2010) argued that the attitude of the project manager is correlated to the success of the project. Therefore, they proposed that the personality of the project manager should be considered as part of the project leadership competencies and attitudes for project success.

Griffith-Cooper and King (2007) stated that communication is the cornerstone of successful change management. They highlighted the four main causes of failure in change management being (a) not articulating the need to change; (b) not communicating the vision adequately; (c) declaring completion too early, and (d) not getting support from leaders below the level of CEO.

For projects to be successful, there must be a proper alignment of content, process, people, and among these factors, the people from various parts of the organisations must be aligned to support the project objectives and processes (Al-Haddad and Kotnour, 2015). These arguments resonate with those put forth by Lam (2009), who proposed that governance structures must be simplified, and the changes must be communicated to all stakeholders to gain acceptance and support. These will then be followed by setting up a project management team, where roles, responsibilities, and performance indicators must be set, tracked, and monitored.

In addition, organisation culture plays a big part to determine the success of change management projects (Exter et al., 2013; Sato and Gnanaratnam, 2014). Hence, the impact of culture should be actively managed and should not be left to chance (Webster, 1992). It is also important to note that organisational culture is created by actions taken by the people, and the leaders can change the culture in their organisations (Whitehurst, 2016).

In summary, the implementation of data analytics must start with a clear purpose or objective, which should be defined by the organisation leaders. The leaders must communicate the purpose and value of implementing data analytics strategies to all the stakeholders to gain acceptance and gather support. This should be followed by the formation of a project team, where a project manager should be appointed. The project manager must be empowered, the expectations of the project must be defined upfront, and criteria must be developed to track the performances. Lastly, organisation culture should be addressed as part of the project.

Segarra et al., (2016) has integrated three frameworks, namely the SWOT analysis, matrix of change, and balanced scorecard to align the people, content and process, and it is shown in Figure 2.6 below. It is a useful guidance to implement changes, such as data analytics strategies, for organisations.

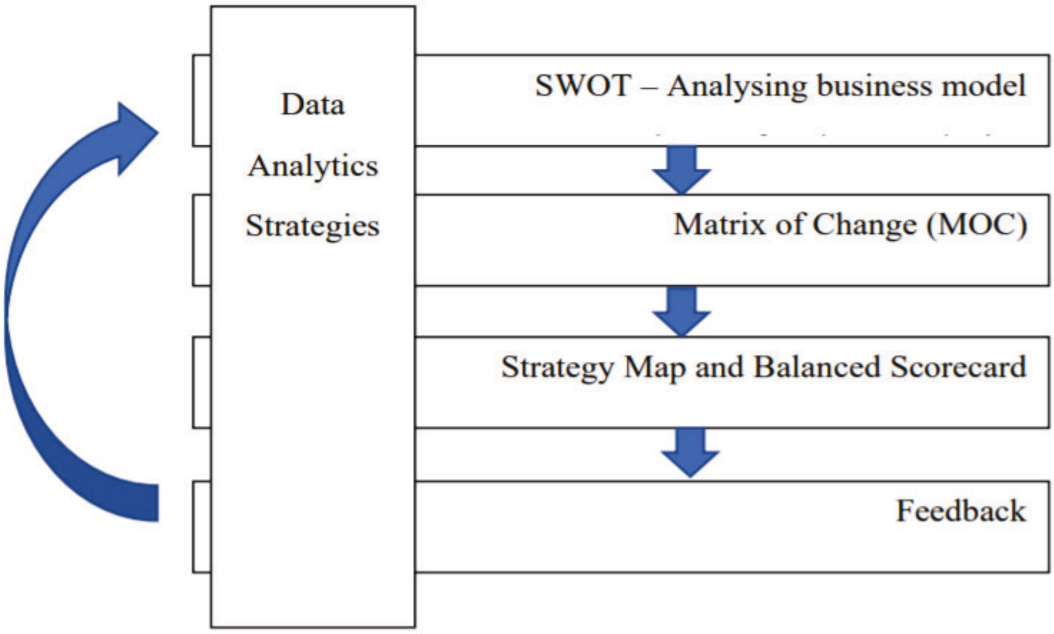


Figure 2.6: Segarra et al. (2016) SWOT analysis, matrix of change, and balance scorecard framework

2.12.1.1. *SWOT Analysis*

Developed by Harvard Business School in the 1960s, SWOT (Strengths, Weaknesses, Opportunities, and Threats) is a widely known tool frequently used by corporations to assess internal processes (Strengths and Weaknesses) to reap benefits (Opportunities) and avoid the risks (Threats) in the external environment.

2.12.1.2. *Matrix of Change*

The Matrix of Change is a tool that captures the existing as well as desired states of organisations. It helps by visualising the transition matrix to identify the best strategy to implement changes.

2.12.1.3. *Balanced Scorecard*

A balanced scorecard enables organisations to formulate strategies in at least four aspects, instead of focusing only on financial targets (Kaplan and Norton, 1996). In adopting a balanced scorecard approach, organisations set targets in financial, customer, internal process, and learning and growth. Hence, a balanced scorecard is an excellent tool to communicate organisation's strategies to its employees (Soderberg et al., 2011).

2.13. Research Gaps

Based on literature reviews, research works in the field of data analytics are performed using commercial organisations, especially the large multi-national organisations, in the United States and Europe. Research gaps are noted as there is little research work on data analytics done using small, not-for-profit organisations in Singapore, a small country located in Southeast Asia.

In addition, it is noted that most of the research works are making wide-ranging recommendations on data analytics implementation using generic scenarios. There is little customisation to the organisations' specific situations, such as culture and structure. Furthermore, these research works have not proven that their recommendations can successfully help organisations implement data analytics strategies. Segarra et al., (2016) has highlighted that research works should focus on practical data analytics strategy implementations, especially for organisations that do not have advanced analytics expertise.

Research work should not be confined to large, commercial organisations, as more can be done to assist small organisations to acquire data analytics skills (Segarrar et al., 2016; Lin, 2014). As research work is lacking on introducing management tools to implement data analytics strategies in a corporation (Segarrar et al., 2016), knowledge can be created from research work on "small data" to help organisations answer specific questions that create values (Kitchin and Lauriault, 2015). Therefore, research values can be created to fill the gaps by performing research work using small, not-for-profit organisations in Singapore that provide practical solutions to implement data analytics strategies.

2.13.1. Research Questions

As a result of the research gaps identified, this research work attempts to answer the following two research questions:

1) What are the challenges and constraints to implementing data analytics strategies in small, not-for-profit organisations in Singapore?
2) How can small, not-for-profit organisations in Singapore, with limited know-how and resources, successfully implement data analytics strategies?

By answering the above research questions, this research project distinguishes itself from other research works in the following aspects:

- Geography - this research is performed in Singapore as opposed to the United States and Europe where most research works are performed.
- Organisation – this research is targeting small, not-for-profit organisations with limited know-how and resources, as opposed to most other research works where large, commercial organisations are used.
- Scope – this research work attempts to provide practical solutions as opposed to generic recommendations in most research works.

2.13.2. Research Aims

Before solving the problems, the first logical step is to identify the underlying root causes. Therefore, this research project will start by identifying the challenges and constraints that small, not-for-profit organisations may encounter when they embark on data analytics strategies. This leads to the following research aims:

1) Identify challenges and constraints to implement data analytics strategies in small, not-for-profit organisations.
2) Evaluate options and provide suitable advice to implement data-driven, contextual marketing strategies for small, not-for-profit organisations.

If the two research aims are achieved, the two research questions will be answered.

2.13.3. Research Objectives

This section sets the research objectives to guide the research work towards the research aims and answer the research questions. The research objectives are:

1) Ascertain challenges and causes for failures to implement data analytics strategies, through the performance of a comprehensive literature review.
2) Analyse key challenges to implementing data analytics strategies confronting the not-for-profit organisation, in Singapore, with limited resources and know-how, through interviews and review of archival records.
3) Identify the required information in the member's database that is required to devise segmentation and contextual marketing strategies.
4) Recommend suitable data analytics tools to implement data-driven, contextual marketing strategies for the small, not-for-profit organisation, bearing in mind the challenges and constraints confronting the organisation.
5) Formulate a change management plan to transform the "one-size fit all" marketing strategy into data-driven, contextual marketing strategies.
6) Through reflection, thoroughly review the drawbacks and provide recommendations for small organisations to enhance their implementation strategies.

It is noted that the first research objective is performed through a comprehensive literature review in this chapter. For the remaining research objectives, the research work will be carried out according to the research methodology outlined in the next chapter. The results will be analysed and addressed in chapter four.

2.14. Frameworks for the Research Project

Before moving to the research methodology, this section will sum up the literature review by identifying the key frameworks to be used for this research work.

The first key framework is the Segarra et al., (2016) framework that integrates the SWOT analysis, matrix of change, and balanced scorecard. It is chosen because it provides guidance to link data analytics strategies with business purposes, and organisations to plan the implementation steps systematically.

The other key framework is the four steps framework proposed by Alibaba Cloud (2018) that advocates organisations "start small" with their data analytics strategies. The framework advocates implementing data analytics strategies in stages as it would allow employees to appreciate the benefits before the organisations scale up for optimisation. The framework was devised with small organisations in mind, and it agrees with McAfee and Brynjolfsson (2012), and Bump (2015) to "start small" and take a stage appoach.

2.15. Summary

This chapter provides a thorough literature review on data analytics and identifies success factors to implement data analytics strategies for small, not-for-profit organisations. It starts by reviewing the trends, historical development, benefits of data analytics strategies before it explores different types of data analytics. The definitions of commonly used terms, such as data analytics, data analysis, data warehouse, data mining, and data science are discussed to provide readers with an understanding of these terms. The challenges to implementing data analytics strategies are covered before research gaps, questions, aims, and objectives are identified. The chapter ends by identifying the key frameworks that will be guiding this research project.

Chapter 3. -Research Methodology

3.1. Preamble

This chapter starts with section 3.2 discussing the nature of business research. Section 3.3 deliberates the research framework and different stages of the research process in the research onion proposed by Saunders et al. (2007), and the choices made by the research student. Ethical issues are considered in section 3.4 followed by the chapter summary in section 3.5.

3.2. Nature of Business Research

Research is defined as the systematic search for relevant information to create new knowledge (Basias and Pollalis, 2018; Tewari and Misra, 2013). Bryman and Bell (2011) opined that business research belongs to the social science disciplines, which also include sociology and psychology. Research methods are not neutral but are related to the manners researchers envisage social reality, and the ways they think reality should be examined (Basias and Pollalis, 2018; Tewari and Misra, 2013; Bryman and Bell, 2011). As the collections and analyses of research data are significant towards the contribution of knowledge, the relationships among theory, research, and researchers are crucial (Bryman and Bell, 2011).

The importance of articulating "research methodology" is underpinned by the fact that research methods are not neutral, as it would enable readers to be informed of the choices made. "Research methodology" refers to the philosophical stance, conceptual perspectives of researches, and the way data are gathered and analysed (Costley et al., 2010). Saunders et al. (2007) proposed that the research methodology be defined using a research onion.

As "methodology" includes defining philosophy, research concept, and data collection, it is different from "method", which normally describes data collection procedures, such as interviews, questionnaires, observations, and experiments (Costley et al., 2010). The table below summarises the difference between "research methodology" and "research method":

Table 3.1: Differences between research methodology and research method

Research methodology	Research method
1. Describes philosophical stance, the conceptual perspective of researches, and data gathering techniques. 2. It includes all the 6 layers in the research onion.	1. Describes data collection techniques, such as interviews, questionnaires, observations, and experiments. 2. It is called research strategy, or layer 3, in the research onion.

3.3. Research Framework

3.3.1. Background

This research project was triggered because the research student has witnessed a vast difference in adopting data analytics in commercial and not-for-profit organisations. In his professional work in a commercial bank, the research student witnesses a wide adoption of 'data analytics" – the Chief Executive Officer has formulated a Data First strategy to change the culture by encouraging managers and employees to use data to make decisions. Training are provided to employees who want to learn new skills.

In contrast, in his voluntary works with not-for-profit organisations, the research student notices that there is little being mentioned about data analytics and using data to support decisions. The lack of data analytics strategies adopted by not-for-profit organisations prompted the research student to assist them to catch up with their commercial counterparts.

Before suggesting effective solutions to help not-for-profit organisations, the reasons for not embracing data analytics must be ascertained. The starting point is to conduct literature reviews. After the searches, it is noted that most of the literature focused on big commercial organisations.

Although recently, there are research works that highlight small, medium enterprises (SMEs) are lagging behind their bigger competitors in launching data analytic strategies, there is limited research work on implementing data analytics strategies for not-for-profit organisations, especially the small ones in Singapore.

As there is little existing knowledge, exploratory research is needed to establish the challenges that are stopping small, not-for-profit organisations from embracing data analytis strategies. One of the not-for-profit organisations in Singapore is chosen for in-depth study. The knowledge gained from the organisation is expected to be relevant for other not-for-profit organisations, especially those with similar setups.

Due to limited prior knowledge in the data analytics field for not-for-profit organisations, going "deep" is necessary to create new knowledge. Semi-structured interviews, which provide flexibility to ask probing questions, are conducted with staff. The interview participants are selected using purposive sampling methodology to focus on staff, who would be involved in the pilot data analytics project, to ascertain the challenges. The primary aim of the first round of interviews is to answer the first research question:

- What are the challenges and constraints to implementing data analytics strategies in small, not-for-profit organisations in Singapore?

The second round of interviews is conducted with all the participants to confirm their understandings. In addition, a preliminary solution to resolve the challenges and launch data analytics strategy for a limited scope is proposed to solicit acceptance by the participants. With the acceptance of the preliminary solutions, it is targeted to develop a prototype to show the staff that the solutions can be implemented with little technical skills. This is to give them confidence to launch data analytics strategy, and concurrently attempt to answer the second research question:

- How can small, not-for-profit organisations in Singapore, with limited know-how and resources, successfully implement data analytics strategies?

The above steps to be taken in this research work can be summarised in Figure 3.1 below.

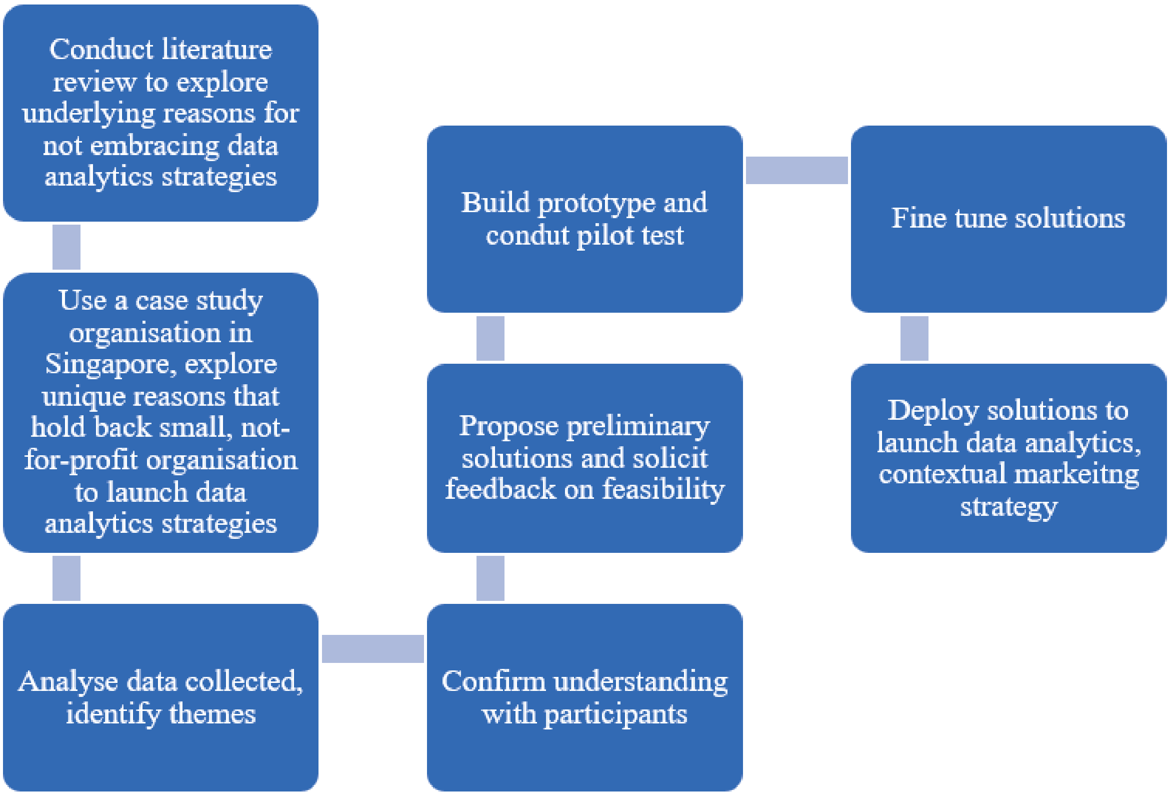


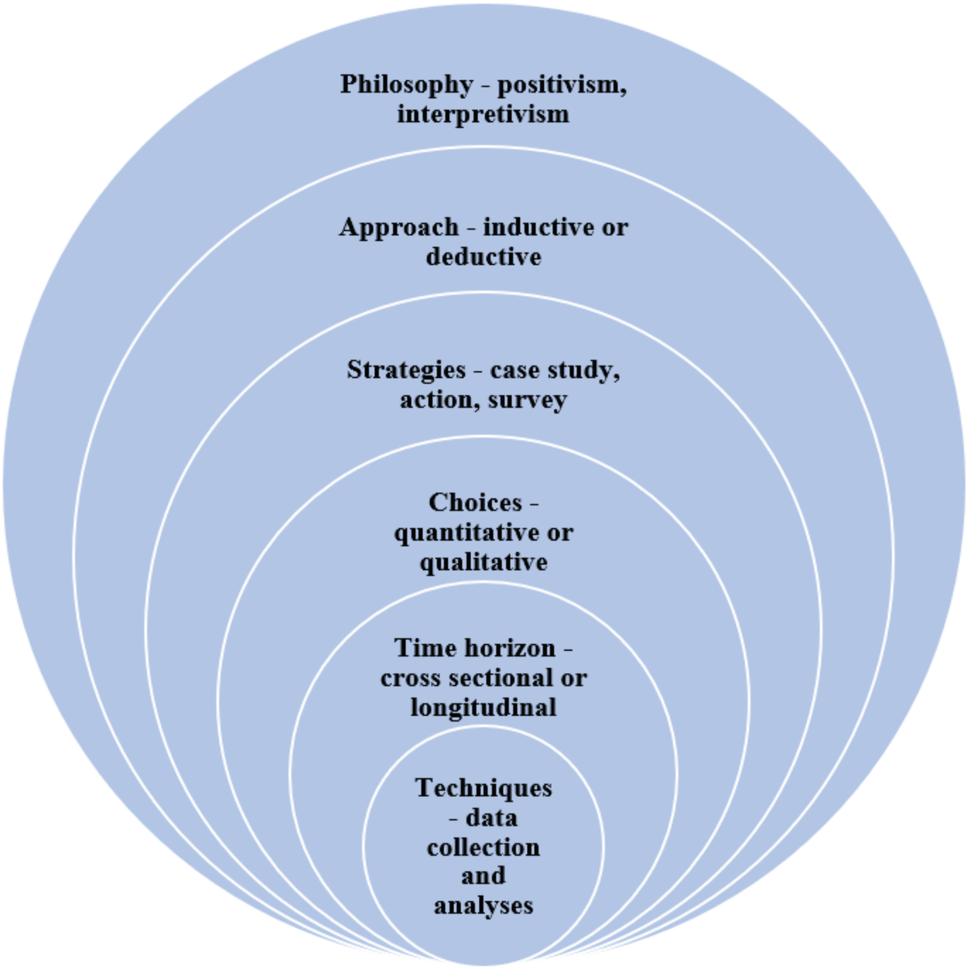
Figure 3.1: Research conceptual framework

3.3.2. Research Onion

Saunders et al. (2007) proposed a research onion where researchers can follow the layers to define their research methodology framework. The research onion has six layers, which start with philosophical stances and end with the research data collection and analysis.

Researchers should start with layer 1 of the onion by defining the research philosophical stances (Johnston, 2014). This should then be followed by layer 2, defining approaches; layer 3, strategies; layer 4, choices; layer 5, time horizons, and layer 6, techniques and procedures. Research methodologies across the six layers must be consistently deployed (Al Zefeiti and Mohamad 2015). The research onion is shown in Figure 3.2 below and each of the layers is discussed in the subsequent sub-sections.

Figure 3.2: Saunders et al. (2007) Research onion



3.3.3. Research Philosophy

Saunders et al. (2007) proposed that researchers should start with the first layer of the research onion, by defining the research philosophical stances. Al Zefeiti and Mohamad (2015) opined that layer 1 of the research onion is the most important because it articulates the believes behind the collections, interpretations, and analyses of data, while Johnston (2014) mentioned that philosophy affects every aspect of the research decisions. Therefore, the articulation of research philosophy enables readers to better understand and assess the researchers' assumptions that underpin their opinions and research conclusions.

Researchers should determine their ontology and epistemology to articulate research philosophy (Anderson et al. 2015; Johnston, 2014), and it should be done before defining the research methods, such as questionnaires, surveys, and interviews (Anderson et al., 2015).

Ontology refers to the nature of reality, the perception of reality, and the role that people play in that reality (Anderson et al., 2015; Bryman and Bell, 2011; Flouris et al., 2008). On the other hand, epistemology refers to the nature and purpose of knowledge (Anderson et al., 2015; Bryman and Bell, 2011).

Bryman and Bell (2011) emphasised that ontology and epistemology cannot be separated from the conduct of business research, as they affect the research approach, including but not limited to, formulation of research questions and the conduct of researches. (Al Zefeiti and Mohamad, 2015; Johnston, 2014; Abdullah, 2012).

Choice for this Research Project

In this research project, the research student seeks to identify the challenges and constraints to implement data analytics strategies for small, not-for-profit organisations in Singapore. This is to answer the research question (1): "what" are the challenges and constraints to implementing data analytics strategies in small, not-for-profit organisations in Singapore? An important aspect of the research question is to ascertain the social actors' views on the strategies to implement data analytics for a not-for-profit organisation. As the social actors have different perceptions about the realities, there is no "single truth" in their views. Therefore, the research student is constructivism (ontology), and interpretivism (epistemology), because he believes that the realities are shaped by the human or social actors.

3.3.4. Research Approaches

In the second layer, researchers are advised to define their research approaches, as either being deductive or inductive (Al Zefeiti and Mohamad, 2015).

3.3.4.1. Deductive Approach

The deductive approach begins with forming a theory or phenomenon, for example, through a literature review. This is followed by collecting data to confirm or reject the theory empirically, e.g., through testable hypotheses (Al Zefeiti and Mohamad, 2015; Anderson et al., 2015; Johnston, 2014). If the data collected consistently confirm the hypotheses, the theories are corroborated; otherwise, the theories are rejected or modified (Anderson et al., 2015).

A deductive approach is suitable for situations when there is a wealth of literature or when the problem is well defined (Anderson et al., 2015). It is also evident that the deductive approach emphasises testing theories and it is usually associated with positivism, who views social reality to exist objectively (Bryman and Bell, 2011).

3.3.4.2. Inductive Approach

The inductive approach starts by building a feel of the situations to form different views of the phenomenon, before data is collected for analysis and to form theories (Al Zefeiti and Mohamad, 2015; Anderson et al., 2015; Johnston, 2014).

The inductive approach is normally adopted when there is limited literature available or when the problem is less well defined (Anderson et al., 2015). The inductive approach emphasises the generation of theories, and it is usually associated with interpretivism, who views social reality to be constantly shifting due to the changes in social actors (Bryman and Bell, 2011).

Choice for this Research Project

As discussed in the literature review sections, most of the researches on data analytics are performed using commercial organisations in the developed countries, but little researches are available using small, not-for-profit organisations in Singapore.

Anderson et al. (2015) have proposed an inductive approach for researches where there is limited literature or when the problem is less defined. Furthermore, the inductive approach, which is closely associated with interpretivism, is adopted when the social realities are constantly shifting due to changes in social actors (Bryman and Bell, 2011).

As the research project involves an area with limited literature, an inductive approach is adopted. The deductive approach, which involves the testing of hypotheses, is not suitable for the research questions in this research project.

3.3.5. Research Strategies

The third layer of the research onion is to define the research strategies, such as case study, action research, survey, and archival research. Research strategies are distinct from research methods, which are concerned with data collections and analyses (Bryman and Bell., 2011).

3.3.5.1. Case Study

A case study is "an intensive study of a single unit to understand a larger class of similar units" (Gerring, 2004, pp 342). It involves data collection from a specific entity or case for in-depth analysis, interpretation, and presentation (Marrelli, 2007; Tellis, 1997). The population of case study research is confined to the unit or case under investigation (Noor, 2008, Gerring, 2004). A case can be defined as a single organisation, location, person, or event (Bryman and Bell, 2011), and it is not meant to research the organisation, but to focus on a particular unit or specific issue (Noor, 2008).

The researchers and participants are considered the actors whose opinions and dynamics as well as the interactions among the actors, are important parts of researches (Tellis, 1997). This, in turn, gives rise to potential ethical issues, where ongoing reflections throughout the research process help to reduce the risks of unethical practices (Marrelli, 2007).

A case study, which provides a richness of data, is seen as a type of research strategies (Lee et al., 2007). It is the preferred research strategy in researches focusing on phenomena within real-life contexts (Yin, 1984), and when little knowledge exists (Marrelli, 2007). Alluding to similar views, Dasgupta (2015) recommended a case study strategy when existing knowledge is limited, or when an in-depth investigation is needed, or when a phenomenon must be studied within a practical context. A case study is an appropriate strategy to answer research questions with "how" and "why" (Dasgupta, 2015).

Most case study researches are linked with the qualitative research method (Bryman and Bell, 2011; Gummesson, 2007), and it has emerged as an important qualitative research approach in many management disciplines (Gummesson, 2000). While Patton and Appelbaum (2003) agreed that the case study is predominately qualitative research, they revealed that quantitative data is also frequently used. This is backed by Mohajan (2018), who claimed that a case study can be both quantitative or qualitative, depending on the purpose of the study. [NB: Quantitative and qualitative research methods are discussed in layer 4 of the research onion.]

The case study method can be applied in exploratory, descriptive, and explanatory researches (Yin, 2003; Tellis, 1997).

- An exploratory case study tends to be a pilot or preliminary research performed before launching full-scale research.
- A descriptive case study is normally used to expand on themes or trends that are already known in other researches.
- An explanatory case study is used to derive a detailed understanding of a certain phenomenon.

A case study can be used to answer exploratory questions because it enables researchers to conduct multi-perspective analyses to achieve holistic understanding and insights (Basias and Pollalis, 2018), and it offers flexibility that is not available in other qualitative research, such as grounded theory (Hyett et al., 2017).

A common criticism against the case study is the lack of ability to generalise its conclusions because it relies on evidence collected on a single case (Tellis, 1997; Singh, 2014; Marrelli, 2007). However, it is argued that high-quality case studies provide useful findings that support generalisation (Noor, 2008; Lee et al., 2007; Gerring, 2004), although Gerring (2004) admitted that case study strategy is less convincing when it is used to confirm theories.

At the commencement of case study researches, gaining access to the organisation and acquiring an understanding of the organisation's structure, culture and politics are critical (Tellis, 1997). Therefore, it is essential to building trust between the researchers and research objects (Singh, 2014). Pre-understanding of the structure, culture, and politics in the orgnanisations provides self-awareness about the personalities that may influent the research processes (Patton and Appelbaum, 2003).

While an interview is the main data collection method in case study researches (Singh, 2014), various sources of evidence should be obtained through documents, archival records, observations, and physical artifacts ((Noor, 2008; Patton and Appelbaum, 2003; Stake, 1995; Yin 1994). Researchers are encouraged to use more than one data collection method for cross-checking and obtaining a broader understanding of issues (Marrelli, 2007).

3.3.5.2. Action Research

Action research is one of the action modes of research that aims to provide conceptual insights into practical problems, through collective reflection and collaboration (Anderson et al., 2015). Specifically, action research aims to resolve problems, and at the same time, contribute to new, practical, and actionable knowledge (Coghlan and Shani, 2014; Mahani and Molki, 2012; Coghlan, 2007; McDermott et al., 2008). There is a persistent call for research to address practical problems and produce actionable knowledge (Coghlan, 2004), and action research provides a strong linkage between theory and practice (Baskerville and Wood-Harper, 1996). As action research can contribute to both professional practice and the body of knowledge (Coghlan and Shani, 2014; Coghlan, 2003), such learning through practice is encouraged (Raelin, 2015; Costley et al., 2010).

Action research is different from processual research, which is called "research on action" because it concerns a process that exists between two points in time (McDermott et al., 2008). In contrast, action research involves planning, taking action, evaluating the action, and taking improved actions (Jarvinen, 2007; Coghlan, 2004; Baskerville and Wood-Harper, 1996). It focuses on generating knowledge while contributing to effective action, and more importantly, the research happens concurrently with the action, hence it is "research in action" (McDermott et al., 2008; Baskerville and Wood-Harper, 1996). Similarly, Coghlan (2004) called it "research in action", as opposed to "research about action" because it is an approach to solve the problem and the research happens concurrently with action.

As action research aims to resolve problems, the researchers are frequently practitioners, who frequently also work in the organisations being researched, hence they are considered insiders (Coghlan, 2007). Coghlan (2003) claimed that the experience of insider researchers is invaluable to the conduct of action researches, which in turn, contribute to knowledge development. Coghlan and Shani (2014) supported the argument as they claimed that the existing knowledge about the researched organisation is integral to resolving real-life organisational problems. Coghlan (2007) advocated that action research involving insiders offers a unique perspective and value.

However, role duality in action research frequently gives rise to role conflicts (Holian and Coghlan, 2013). The interdependence between researchers and those being researched can be a huge challenge in action research (Coghlan and Shani, 2005). Therefore, action research should be carried out in collaborative environments and relationships (Zeni, 1998; Kelsey, 2004, Holian and Coghlan, 2013). It is argued that positive relationships are critical to solve practical problems, and generate new actionable knowledge for scholarly as well as practitioner communities (Coghlan, 2003; Coghlan and Shani, 2014). Adding to the argument that collaboration is paramount, Coghlan (2004) highlighted that action research is participative, as the participants are actively involved in planning, taking action, evaluating action, and learning from the action. As such, action research is "research with people" instead of "research on people" (Coghlan, 2004).

Action research involving insiders has emerged as an important and established way to understand and change organisations (Coghlan, 2007). Due to the criticality of relationships between researcher and participants, it is important to avoid unethical practices, such as spying on others (Coghlan, 2003). There should be mutual respect and avoid harming any of the actors (Coghlan and Shani, 2005). The relationships must be built on trust, empathy, and non-exploitative (Punch, 1994). In addition, the researcher needs to be politically astute to manage the relationships, not only with participants but also with other parties in the researched organisations (Coghlan, 2003; Coghlan and Shani, 2005). Researchers need to work on the political system, as without proper management, politics can jeopardise the research outcomes (Coghlan and Shani, 2005).

Action research is rated as the most demanding and far-reaching research method for case studies (Gummesson, 2000). This illustrates that the action research method can be adopted in conjunction with a case study. To overcome its challenges, a systemic, design-based framework is proposed for action research (Coghlan and Shani, 2014; Coghlan and Shani, 2005). The framework suggested that four key features, namely, context, inquiry mechanism, inquiry cycle, and outcomes, be clearly defined. The inquiry cycle includes diagnosing, planning, implementation, and evaluation (Coghlan and Shani, 2005).

Most of the researchers engaging in action research are insiders (Coghlan, 2007), they influence the outcome of the research. Coghlan and Shani (2005) emphasised the importance for the researcher to be self-reflexive. This involves consciously self-examine the subjectivity, interpersonal response, and emotion as well as the researcher's relationship with other participants (Zeni, 1998). It is also important for the researcher to define his roles clearly in the research (Coghlan and Shani, 2005). This is because role conflicts are likely to arise, as the expectations and commitment levels as an employee are likely to differ from those of a researcher (Holian and Coghlan, 2013; Coghlan, 2007). Lastly, it is also important for action researchers to do reflection, which is to record their experience and share the lessons with the community (Kelsey, 2004). Holian and Coghlan (2013) stressed that integrity, ethics, and expertise of the researcher are key success factors for action research.

Qualitative research methods can be used for action research, and the sample size can be small (Zeni, 1998). As action research focuses on resolving problems and creating knowledge in action, it is situational, the data is interpreted, and the researcher is a change agent (Coghlan, 2004). This is in contrast to the positivist stance adopted for quantitative research methods, where knowledge should be universal, and the researcher is a detached observer (Coghlan, 2004). Due to the usual small sample size, it is questionable whether the knowledge can be generalised. Baskerville and Wood-Harper (1996) argued that as long as the findings are valid, the generalisation is legitimate.

In summary, insider researchers who adopt action research must deal with challenges such as role duality and organisation politics (Coghlan, 2007). Holian and Coghlan (2013) concluded that judgements must be made on reasonable grounds, and decisions and actions are taken must be on responsible grounds.

3.3.5.3. Survey

Survey research is usually deployed to collect quantifiable data, through a questionnaire or structured interview, to establish the connection between two variables (Bryman and Bell, 2011), and establish causalities (Fox et al., 2017).

There are two main types of survey design, namely cross-sectional and longitudinal (Fox et al., 2017). The cross-sectional survey involves collecting data at one single point in time, whereas the longitudinal survey involves collecting data at two or more points in time. The longitudinal survey is deployed to ascertain the changes in attitude, behaviour, or value over time (Bryman and Bell, 2011). Using a different prism, Forza (2002) named three types of survey. The first type is an exploratory survey which takes place in the early stage of research to gain preliminary understanding. The second type is a confirmatory/explanatory survey which is used to test theories. The third type is a descriptive survey which is used to the described phenomenon in a population.

Choice for this Research Project

In this research project, an objective is to assist one not-for-profit organisation overcome practical challenges to launch data analytics strategies, as the lessons learnt are expected to add value to the body of knowledge by benefiting other similar organisations. The research student targets to acquire knowledge through practical implementation advocated by Raelin, (2015), and Costley et al. (2010).

This research project will adopt a case study research strategy, which provides conceptual insights into practical problems (Anderson et al., 2015), contributes to the new, practical, and actionable body of knowledge (Coghlan and Shani, 2014; Mahani and Molki, 2012; Coghlan, 2007; Coghlan, 2003; McDermott et al., 2008), provides a richness of data (Noor, 2008; Lee et al., 2007), focuses on phenomenon within real-life context (Yin, 1984), provides insights when little is known (Marrelli, 2007; Dasgupta, 2015), and allows in-depth investigations (Dasgupta, 2015).

In addition, the case study is a suitable research strategy, because it is catered to answer research questions with "how" and "why" (Dasgupta, 2015). The research student will work with the social actors in a small, not-for-profit organisation in Singapore, to fully understand the challenges that the organisation faces, before recommending steps to launch its data analytics strategies.

3.3.6. Research Choices

In the fourth layer, researchers have to make research choices among quantitative, qualitative, or mixed methods (Bryman, 2006). The determination of research choices should come after philosophy and research strategy (Anderson et al., 2015). The selection of research methods depends on the nature of research questions, objectives, and topics (Al Zefeiti and Mohamad, 2015; Johnston, 2014; Cook and Cook, 2008), which in turn, are influenced by researchers' underlying believes, or ontology and epistemology (Johnston, 2014; Bryman and Bell, 2011).

It is often argued that quantitative research begins with the assumption that appropriate variables can be identified in advance and can be measured. This makes quantitative research likely to be deductive, objective, variable-based, hypothesis-driven, and theory testing (Kerr et al., 2010). In addition, quantitative research accounts for many cases and few variables (O'Day and Killeen, 2002).

On the other hand, qualitative research tends to be inductive, subjective, case-based, and theory building (Kerr et al., 2010), and it tends to account for fewer cases but many variables (Cook and Cook, 2008; O'Day and Killeen, 2002).

In comparison, quantitative research tends to test theory and thus confirmatory, while qualitative research tends to be an exploratory study that builds theory (Dasgupta, 2015).

3.3.6.1. Quantitative Research

The objectives of quantitative research are typically descriptive and explanative (Al Zefeiti and Mohamad, 2015; Abdullah, 2012). It is generally used in situations where measurement of the phenomenon is important, but difficult to measure or observe directly (Cook and Cook, 2008). In quantitative research, statistics and numerical data are usually used to conduct empirical and systematic investigations (Basias and Pollalis, 2018). It focuses on describing factors such as the nature of data collected, sampling techniques, sample size, and analysis plan (Al Zefeiti and Mohamad, 2015). To sum up, quantitative research entails a deductive approach and it is typically used for testing theories. (Basias and Pollalis, 2018; Dasgupta, 2015; Bryman and Bell, 2011; Kerr et al., 2010).

Advantages that can be attributed to quantitative research include the development of numerical indicators to facilitate comparisons, simplifies the processing of a large amount of data with lesser influence by personal feelings (Basias and Pollalis, 2018). As quantitative research normally collects a large set of data, it is argued that the data is representative of the population, and therefore, the findings can be generalised, and they can be replicated (Goertzen, 2017).

In addition, it is argued that quantitative research is value-free, and therefore, it is not influenced by personal feelings or opinions (Basias and Pollalis, 2018). However, it is noted that this view is challenged by Zyphur and Pierides (2019), who argued that research is value-laden, and not value-free. Value is defined as the feelings or beliefs of the researcher (Bryman and Bell, 2011). Syphur and Pierides (2019) claimed that the research process cannot escape the embodiment of the people who perform the research, therefore, quantitative research cannot be value-free. Supporting the view, Patton and Appelbaum (2003) argued that the bias of the researcher and participants can impact the outcome of quantitative research. For example, the outcomes of quantitative researches can be influent by sample manipulation, data tampering, poor survey construction, and dishonest responses.

The most commonly used data collection method for quantitative research is the structured approach, such as tick-box questionnaires, structured interviews, or observation checklists (Costley et al., 2010). The advantages of a structured approach include comparability and easier statistical analysis, however, their greatest disadvantage is the lack of flexibility (Costley et al., 2010).

One of the main critics of quantitative research is the lack of explanation on the “why” part of the phenomenon because it may not provide the reasons behind the occurrence (Goertzen, 2017).

3.3.6.2. Qualitative Research

The objectives of qualitative research are typically explorative and descriptive (Al Zefeiti and Mohamad, 2015; Dasgupta, 2015), and the aims are to develop understanding, especially in areas where there is little knowledge or research (Basias, 2018; Kerr et al., 2010). As qualitative research facilitates the unlocking of new themes (Abdullah, 2012), it is usually adopted to investigate issues where views, attitudes, and perceptions of the social actors are critical (Al Zefeiti and Mohamad, 2015; Kerr et al., 2010). It can also help to understand complex interactions among participants, between participants and their institutions, as well as open opportunities for unexpected findings and discovery (O'Day and Killeen, 2002).

Acknowledging that qualitative researches are not value-free, qualitative researchers do not need to distance themselves from the participants, instead, they are encouraged to adopt an active learner stance to tell the story from the participants’ point of view (O'Day and Killeen, 2002). In this regard, qualitative research is closely associated with interpretivism and constructionism in terms of epistemological orientation and ontological orientation respectively (Bryman and Bell, 2011).

The data collected through qualitative methods are descriptive, in many forms, which could include documentation, observations, or interviews (Mohajan, 2018; Kerr et al., 2010). In general, qualitative research accounts for fewer cases and many variables (O'Day and Killeen, 2002), data collected in qualitative research are normally more time-consuming to analyse (Mays and Pope, 1995). Therefore, it is important to have specific goals in mind when collecting and analysing qualitative data (Kerr et al., 2010).

Common critics of qualitative research include its lack of scientific rigor, being strongly subject to researcher bias, and lack of generalisability (Mays and Pope, 1995). However, it is argued that the criticisms are made against the unintended purposes of qualitative research, which are not meant to search for truth, test hypotheses, or verify theory (Borman et al., 1986). To overcome the disadvantages, qualitative researchers can systematically record their interpretation and analysis, together with clear research questions, data sources, and sampling strategy to allow readers to assess the reliability and quality (Borman et al., 1986).

It would also be useful for qualitative researchers to set aside periods of detachment from the research fieldwork to regain perspective (Borman et al., 1986). When used properly, qualitative research can generate theories (Bryman and Bell, 2011). It is further argued that qualitative research attempts to understand the experiences of the participants as insiders, therefore, the findings are grounded to the realities and hence, can provide useful knowledge with practical usage (O'Day and Killeen, 2002).

Adapting from Bryman and Bell (2011), the table below shows the differences between quantitative and qualitative research strategies:

Research Onion		**Quantitative**	**Qualitative**
Layer 1	**Ontological orientation**	Objectivism	Constructivism
	Epistemological orientation	Positivism	Interpretivism
Layer 2	**Research approaches**	Deductive, testing of theory	Inductive, generation of theory

Action research, case study, grounded study, and narrative research are examples of qualitative research methods (Mohajan, 2018).

3.3.6.3. Mixed-Method

There are advocates to combine quantitative and qualitative research methods in one research. Miller and Cameron (2011) studied the research methods adopted by researchers across a wide variety of disciplines and noted that the number of researches adopting mixed method research is growing. Abdullah (2012) confirmed that the use of mixed-method is also growing in Asia.

The combination of quantitative and qualitative methods in one research can be called mixed method, or multi-methods, multi-strategy or mixed methodology (Bryman, 2006). However, Miller and Cameron (2011), and Johnson et al. (2007) disagreed with Bryman (2006), as they argued that it is important to differentiate the terms mixed-method and multi-methods. The mixed-method should involve the integration of quantitative and qualitative methods in a single research, on the other hand, multi-methods are researches that adopt more than one research methods or data collection techniques, where the methods or techniques could be in the same paradigm (Miller and Cameron, 2011). For example, structured interviews combined with surveys which are both quantitative data collection methods, are considered multi-methods, but not a mixed method.

Johnson et al. (2007) noted that there are various definitions for mixed-method, but the researchers must include both quantitative and qualitative methods in the same research question to be considered as the mixed method.

There are also various combinations of mixture between the quantitative and qualitative methods. Johnson et al. (2007) suggested that there are the broadly qualitative dominant mixed method, equal status mixed-method, and quantitative dominant mixed method.

The reasons for adopting the mixed method include triangulation, complementarity, development, initiation, and expansion (Bryman, 2006). Adopting both quantitative and qualitative methods in the same research allows corroboration of information collected using both methods to strengthen the arguments while offsetting the weaknesses of both (Bryman, 2006). Therefore, some argued that mixed-method also enable better understanding and description as it provides a fuller picture than using either pure quantitative or qualitative methods (Johnson et al., 2007; Abdullah, 2012).

Critics of mixed methods include time-consuming (Johnson et al., 2007) and unclear ontology and epistemology (Morgan, 2007). While time-consuming can be overcome with better planning and practices, it is almost impossible to combine the two methods without violating the philosophical principles (Morgan, 2007).

Choice for this Research Project

As the attitudes and perceptions of social actors are critical, qualitative research is the recommended choice (Al Zefeiti and Mohamad, 2015; Kerr et al., 2010), and it helps to understand complex interactions among participants, between participants and their institutions (O'Day and Killeen, 2002). In this regard, qualitative research is closely associated with interpretivism and constructionism in terms of epistemological orientation and ontological orientation respectively (Bryman and Bell, 2011). It is also argued that qualitative research opens opportunities for unexpected findings and discovery (O'Day and Killeen, 2002).

Given the above, qualitative research is suitable for this research project, as there is little knowledge in launching data analytics for small, not-for-profit organisations in Singapore. This research project requires the research student to identify the views, attitudes, and perceptions of those involved in the marketing strategies for the case study organisation. Qualitative research is also more aligned with the research student's interpretivism and constructivism in terms of epistemological and ontological orientations respectively.

The research student has also considered mixed research which provides benefits such as triangulation (Bryman, 2006), better understanding, and description (Abdullah, 2012; Johnson et al., 2007). Weaknesses of quantitative and qualitative methods can also be offset by adopting the mixed method, as information can be corroborated (Bryman, 2006). However, as mixed-method has an unclear stance on ontology and epistemology (Morgan, 2007), it may not be advisable to combine the two methods that may violate the philosophical principles.

3.3.7. Research Time Horizons

In the fifth layer, decisions should be made over the duration covered by researches, that is, the coverage over the short or long term. The short-term researches, also called cross-sectional researches (Fox et al., 2017), including data collected at one point in time (Bryman and Bell, 2011). On the other hand, long-term researches, also called longitudinal researches (Fox et al., 2017), typically aim to understand a population over time when there are changes (Bryman and Bell, 2011). In the fields of business and management studies, both cross-sectional and longitudinal types of research can be used in either quantitative or qualitative researches (Bryman and Bell, 2011).

Choice for this Research Project

Cross-sectional research is adopted for this research project as it collects data at a point in time, to understand that challenges to launch data analytics marketing strategies for a small, not-for-profit organisation in Singapore. Longitudinal research can be used for future research works to ascertain the impact of the new marketing strategies after it has been launched by the organisation.

3.3.8. Research Techniques and Procedures

In the final or sixth layer of the onion, researchers have to reflect on the previous layers to decide on the most appropriate research design for data collection and analysis, by defining the data sources, data collection methods, sampling strategies, and response rates (Bryman and Bell, 2011). Data collection methods include the techniques, tools, and procedures, such as questionnaire, observation, interview, and text analysis, to collect data (Smith, 2009).

3.3.8.1. Data Source and Case Study Organisation

The research student has chosen ABC, a small, not-for-profit, professional body in Singapore as the case study organisation, because it suits the criteria of the research questions. In addition, ABC has the intention to improve its member engagement strategies. Specifically, it has a "one-size-fits-all" marketing strategy where it sends mass messages to its members to market its training courses.

With the advances of technology, data analytics provide options for ABC to adopt targeted and customised marketing strategies. The available options drive ABC to review its strategies and as a result, it plans to improve its strategies to market training courses. ABC wants it as a starting point because training courses account for more than 75% of its annual revenue.

However, with limited skills and know-how, ABC needs help to implement data analytics strategies. As a volunteer at ABC, the research student wants to help the organisation pick up new skills and move ahead with better marketing strategies. Many organisations similar to ABC are facing the same challenges, as have little resources and know-how.

ABC employs 11 full-time staff who are responsible for the day-to-day operations of the organisation. It is headed by the Executive Director, who is the most senior staff, reporting to the board of governors. Two of the staff are responsible for organising training courses, which include logistic arrangements, liaising with the trainers as well as marketing the courses to participants. The other staff members are responsible for membership, information technology, marketing, accounting, publication, administration, and special projects.

3.3.8.2. Data Collection Method

There are two broad categories of data collection methods. The first category is the structured approach, where the data classifications are determined upfront for respondents to tick the box. The second category is the open approach, where respondents have little restrictions to voice their opinions (Costley et al., 2010). The open approach would facilitate more in-depth discussions but would require more time for analysis, and it is less suitable for quantitative research (Costley et al., 2010).

In qualitative research, there are various data collection methods, such as interviews, observations, and documentations (Kerr et al., 2010).

Questionnaire

A questionnaire is an example of a structured instrument, where the respondents have to answer the question in a specific manner (Bryman and Bell, 2011), therefore, it is more aligned to quantitative research, which is confirmatory (Dasgupta, 2015). Being aligned to quantitative research, the number of participants tends to be large (Oplatka and Hemsley-Brown, 2004).

Interview

Compared to the questionnaire, interviews are more aligned to qualitative research, which tends to be exploratory (Azorin, 2007). As qualitative interviews can reveal complexities and contradictions that are fundamental to social phenomena, they are adopted when researchers seek to understand phenomena, attitudes, or opinions, especially when little is known about the subject (Rowley, 2012; Oplatka and Hemsley-Brown, 2004; Shahaida et al., 2009). It is also the most important data collection method in case study researches (Tellis, 1997).

Observation

Tellis (1997) warned against over-reliance on a single informant, suggested authenticating through data collected from other sources. Oplatka and Hemsley-Brown (2004) proposed using observation to collect data on top of questionnaires and interviews; as he opined that questionnaires and interviews rely on the interpretations of the respondents.

Choice for this Research Project

As there is little research on data analytics using small, not-for-profit organisations in Singapore, semi-structured interviews with an open approach is considered the suitable data collection procedures that seek to understand phenomena, attitudes, and opinions (Rowley, 2012), especially when there is limited prior researches in the topic (Rowley, 2012; Shahaida et al., 2009; Oplatka and Hemsley-Brown, 2004). The interview is also an important data collection method for case studies (Tellis, 1997).

The questions to be used for semi-structured interviews are attached in Appendix 1 for reference. After conducting the semi-structured interviews, the following steps, which are recommended by SAGE Research Methods Datasets (2015), will be performed to identify common themes raised by the participants:

(a) Typing out the interview transcripts and confirm the accuracy and completeness with participants.
(b) Reading the confirmed transcripts several times to analyse and identify the initial codes.
(c) Reviewing the initial codes to categorise themes to identify common ones.

The common themes identified will be compared against those noted in the literature review. By doing so, the following research question, aim, and objective are expected to be addressed:

- Research question - What are the challenges and constraints to implementing data analytics strategies in small, not-for-profit organisations in Singapore?
- Research aim - Identify challenges and constraints to implement data analytics strategies in small, not-for-profit organisations.
- Research objective - Analyse key challenges to implementing data analytics strategies confronting the not-for-profit organisation, in Singapore, with limited resources and know-how, through interviews and review of archival records.

In a case study, it is advisable to use other data collection methods to supplement those collected via interviews (Oplatka and Hemsley-Brown, 2004; Tellis, 1997), hence direct observation and archival records are used to authenticate information collected through semi-structured interviews.

3.3.9. Adopted Research Framework

Using the research onion, this section summarises the adopted research methodology:

Layer	**Research methodology**	**Adopted for this research project**
1	Philosophy	Constructivism (ontology), interpretivism (epistemology)
2	Approach	Inductive
3	Strategy	Case study
4	Choice	Qualitative
5	Time horizon	Cross-sectional
6	Technique and procedure	Structured interviews, observation, archival record

The layers are also presented in terms of research onion in Figure 3.3 below

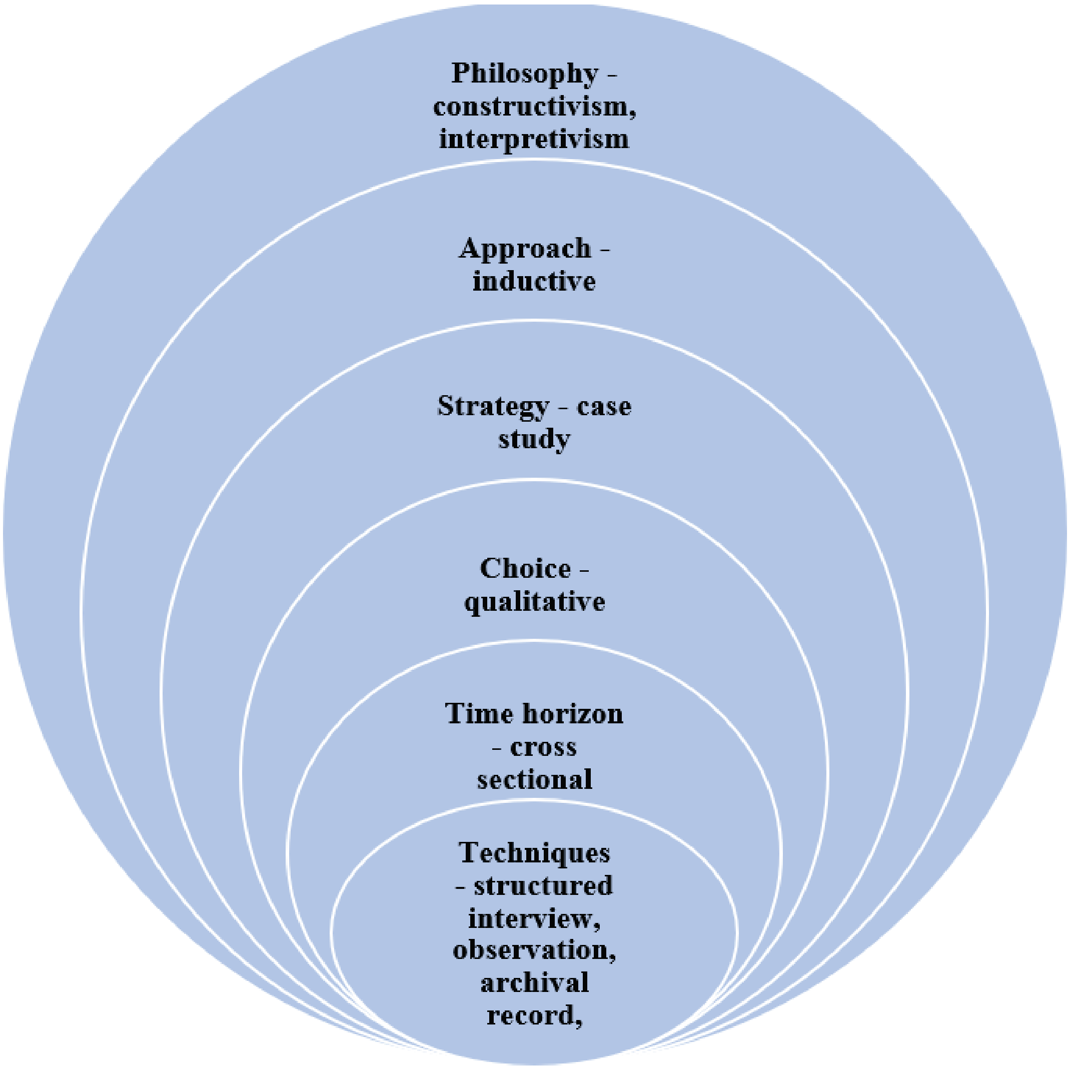


Figure 3.3: Adopted research methodology presented in research onion

3.3.10. Sampling Strategy

Before embarking on data collection, a sampling strategy should be designed (Gutterman, 2015; Tewari and Misra, 2013). Sampling means selecting a portion of the total number of units for testing to draw general conclusions that apply to the entire body (Al Zefeiti and Mohamad, 2015). A good sampling strategy will help to select samples that are representative of the population with a reasonable level of confidence, and the costs of collection and analyses viable for the research budget (Tewari and Misra, 2013). However, researchers must be aware that the sample selected may not fully represent the population, this is referred to as sampling error, which cannot be fully eliminated (Bryman and Bell, 2011).

The two broad categories of sampling methods are "probability" and "non-probability" methods (Al Zefeiti and Mohamad, 2015). Random and systematic ways of selecting samples are examples of probability sampling methods where every member of the population has an equal chance of being selected (Al Zefeiti and Mohamad, 2015). The main advantage of using the probability sampling method is the ability to generalise its findings because they are supported by statistics (Bryman and Bell, 2011).

In qualitative studies, the sample sizes are generally smaller than those in quantitative studies, because qualitative studies are more concerned about the meaning rather than making generalised hypotheses (Mason, 2010).

Beuckelaer and Wagner (2012) argued that small sample sizes, which are defined as those smaller than 30 observations, may lead to representativeness bias, lack of statistical power, and unstable results. However, Hood (2006) disagreed, and argued that while the manners to generalise using small, non-probability samples should differ from that using probability samples, it does not mean that findings using small, non-probability samples cannot be generalised. It is further argued that a non-probability sample should be used when it is impossible to select a random sample from the population, for example, a purposive sample can be adopted (Hood, 2006).

The purposive sampling method, which does not involve a big sample size, is frequently adopted for qualitative studies (Kerr et al., 2010). It is also noted that in the case study, the population size is usually not big enough for random sampling to apply, hence, purposive sampling is more suitable (Marrelli, 2007). Purposive samples are productive and focus on providing answers to the research questions (Kerr et al., 2010) and it is used for studies concerning specific phenomena (Ahlstrom et al., 2004).

Mason (2010) revealed that many research students have used sample sizes that were larger than necessary. There are concerns that superfluous samples may consume unnecessary resources while sacrificing the depth of the research (Gutterman, 2015; Marshall et al., 2013). The concept of saturation, which happens when the collection of new data add no further value to the studies, can help to avoid superfluous samples (Gutterman, 2015; Mason, 2010; Kerr et al., 2010). However, it is noted that the justifications for the selected sample size should be articulated (Gutterman, 2015).

Choice for this Research Project

The case study organisation employs only 11 staff, therefore, random sampling cannot be applied. Instead, smaller sample sizes are suitable for this research because inductive and qualitative researches are more concerned about the meaning rather than confirming hypotheses (Mason, 2010). Furthermore, the quality of the data collected is more important than the sample size (Marshall et al., 2013).

The purposive sampling method is suitable for case study researches (Kerr et al., 2010; Marrelli, 2007), especially those concerning specific phenomena (Ahlstrom et al., 2004). In this research project, staff who are responsible for training courses, marketing, and information technology are approached to provide relevant insights. On the other hand, the staff who are responsible for accounting and administration are not invited to participate because their experiences and job scope are not directly relevant.

As pointed out by Mason (2010), many research students have used superfluous sample sizes, the research quality may suffer because unnecessary resources may be consumed by the superfluous samples, leading to sacrifice in the depth of the research (Gutterman, 2015). Purposive sampling method enables the research student to stay focus and avoid selecting superfluous samples. In determining the sample size, the research student was guided by saturation of knowledge, when the addition sample adds marginal value to the research (Gutterman, 2015; Kerr et al., 2010; Mason, 2010).

By choosing a purposive sample with known characteristics would allow research findings to be generalised across different populations with similar characteristics (Hood, 2006). The generalisation can be achieved with 15 to 30 interviews conducted in single case studies (Marshall et al., 2013), and with 2 to 3 interviews per person (Morse, 2000). For example, Heathcote et al., (2020) conducted three rounds of interviews with five individuals for their research.

As this research project involves designing a data analytics tool to assist the not-for-profit organisation to launch a data-driven marketing strategy, interviewing each participant 2 to 3 rounds is akin to Design Science Research methodology, recommended by Peffers et al. (2007).

3.3.11. Design Science Research (DSR)

DSR is an iterative research process that includes ideation, prototyping, and implementation (Patricio et al., 2019). Although it was initially developed to solve problems relating to information systems (Peffers et al., 2007), it is now used to understand organisations' real-world problems before creating solutions to solve them (Gregor and Hevner, 2013), as DSR involved a full spectrum of action-oriented research that aims to develop new frameworks or methods (Teixeira et al., 2019).

This research project explores launching data analytics strategies for not-for-profit organisations where little research has been performed, hence, it is expected that new frameworks or methods may be required. DSR is considered a suitable approach, as it is designed not only to explore, describe and explain an issue but also to prescribe solutions (Dresch et al., 2014).

There are many different approaches to conduct DSR (Heathcote et al., 2020). Teixeira et al. (2019) proposed a three-cycle framework by firstly, identify the problems; secondly, design and develop solutions; thirdly, apply the solutions and evaluate the outcomes, while Dresch et al. (2014) made it a six-steps framework with (a) problem definition, (b) solution, (c) development, (d) evaluation, (e) value addition and (f) communication.

Being iterative, participatory, multi-disciplinary, and human-centric, DSR is an excellent approach to understand the challenges and perspectives of multiple actors to develop holistic solutions (Teixeira et al., 2019). Interview iterations and involvements of individuals with ranges of perspectives optimise the development of artefacts to propose solutions (Heathcote et al., 2020).

3.3.12. Triangulation

This research project is adopting the case study approach, using one small, not-for-profit organisation. The research student is mindful that due to the small staff strength (11 staff) in the organisation, it is not practical to adopt random sampling. Instead, the purposive sampling method is adopted as it is recommended by Kerr et al. (2010), Marrelli (2007), and Hood (2006). Under such constraint, it is apt to address whether the findings from such a small sample size can be generalised.

It is a common criticism to generalise findings based on one case study (Singh, 2014; Marrelli, 2007; Tellis, 1997). However, it is argued that samples may be selected from a single organisation (Marrelli, 2007; Tellis, 1997), location, person, or event (Bryman and Bell, 2011). Generalisation can be done as long as the findings have high quality (Noor, 2008; Lee et al., 2007; Gerring, 2004).

The other constraint on the ability to generalise relates to the small sample size, which is defined as those smaller than 30 (Beuckelaer and Wagner, 2012). However, the ability to generalise valid findings should not be limited merely because of the small sample size (Baskerville and Wood-Harper, 1996).

Although noting that case study using one organisation and the small sample size are not affecting the ability for generalisation, the research student will conduct a second round of interviews with all the participants to confirm the understanding from the first interviews. The second round of interviews is aligned with the iterative and participatory approach proposed by DSR, as discussed in the section above. The confirmation of understandings will also serve as triangulation.

3.4. Ethical Considerations

3.4.1. Insider Researcher

The research student is an active volunteer in the case study organisation for this research project, therefore, he is considered a practitioner-researcher. Practitioner-researchers are practitioners who participate and pursue scholarly research (Wasserman and Kram, 2009). Some of the other terms used to describe “practitioner-researcher” are researcher-practitioner, scientist-practitioner, scholar-practitioner, scholarly-practitioner, reflective practitioner, and practitioner-theorist (Wasserman and Kram, 2009).

As practitioner-researchers frequently use the organisations who hire them in their professional roles, to perform their scholarly researches, Costley et al. (2010) used the term “insider-researcher”. As the research student is an active volunteer in the case study organisation, the term “insider-researcher” will be used, although it is understood that it can be used interchangeably with “practitioner-researcher”.

Mathiassen and Sandberg (2013) are strong advocates of combining practical experiences with scholarly researches and they opined that work by practitioner-researchers will complement the work performed by academic researchers. While insider-researchers have advantages, the dual roles raise challenges and potential ethical issues (Costley et al., 2010). Firstly, the researchers should make sure that the benefits of the research are not confined only to the individuals, but should also benefit the organisation as well as the wider community (Anderson et al., 2015). Secondly, the researchers should avoid using established relationships to pressurise staff members in the researched organisation into the obligation to participate in the research (Costley et al., 2010).

In addition, ethical issues such as confidentiality and harm should be addressed. Unluer (2012) warned against overlooking routine behaviours and making invalid assumptions as an insider-researcher.

Greene (2014) proposed researchers adopt triangulation and reflexivity to minimise the shortcomings of being an insider-researcher. Triangulation involves obtaining evidence and information from various sources for authentication. The term “reflexivity” can be vague, it is essentially the exploration and acknowledgement of the relationships between the researcher and other actors in the research (Brannick and Coghlan, 2006).

Analytical reflexivity which includes defining the researchers’ roles, articulating the ontology and epistemology, providing data for verification, accounting for the decisions made, amongst others, is recommended by Smith (2009). Mahadevan (2011) emphasised that the researchers’ roles and styles of writing should be included as part of reflexivity. However, it is important to note that reflexivity provides awareness of the relationships between the researchers and the other actors, but it does not eliminate all the shortcomings (Smith, 2009).

Steps taken for this Research Project

As noted, the research student is an insider-researcher, who recruits research participants from the organisation in which he volunteers. However, as a volunteer, the research student has no executive authority and does not influence the staffs’ appraisals and remunerations. This mitigates the potential conflict of interest and pressure for the staff to participate in this research project against their wills.

In addition, due considerations are given to factors such as benefits and harms, informed consent, and confidentiality. The research project is beneficial to all the parties involved in the project, as the organisation will benefit through the implementation of more advanced marketing strategies using data analytics; the participants will benefit by learning new skills such as data analytics; project sponsors will benefit through demonstration of their leadership skills; the community will benefit as the lesson learnt from the case study can be shared with similar organisations to launch data analytics strategies. The organisation and participants are also expected to enjoy a lighter manual workload due to automation through analytics.

While it is expected that this research project should not harm the participants, care is taken to treat all participants with respect and the purposes of the project are explained to maintain transparency (Anderson et al., 2015). The research student acknowledges that practitioner research is political (Coghlan and Shani 2005), therefore politically astute is necessary for this research project. Furthermore, this project is undertaken in the spirit of collaboration, mutual benefits, as described above, are the foundations.

Notwithstanding the mutual benefits, the participants are given time and opportunity to clarify, ask questions, and think about the value of the research before they gave their consent. Participants are aware that they can stop answering any question if they do not feel comfortable during the interviews. They also have the right to reject the voice recording of their interviews. In addition, they are briefed on their rights to withdraw from the project within a week after they have given their consent.

The research student acts as an equal partner, and not an expert, to the participants in this research project. The research student's role and expectation are articulated upfront and reinforced during the research, as suggested by Coghlan and Shani (2005) to build trust and facilitate willingness in the participation. In addition, the objectives of the study, as well as the purpose of the information collected, are explained to the participants, as recommended by Costley et al., (2010).

For maintenance of confidentiality, the names of organisation and participants are not included in the research project or publication thereof. The participants' names are "coded" to ensure anonymity. Due to the size of the case study organisation, special care is taken to maintain confidentiality in a small team. Confidentiality is discussed with the participants during the recruitment stage and is reinforced throughout the process, as recommended by Olivier (2009) and Petrova et al. (2014).

In addition to the above, all interviews are conducted in a private setup, away from disturbance and overlooking. Due to COVID-19, interviews are conducted via a secured platform, Zoom, with password protection enabled.

Interviews are conducted in two rounds for all the participants. In the first round, participants are asked to share their views and anticipated challenges for the case study organisation to launch data-driven, contextual marketing strategy for its training courses. In the second round, the research student summarises the challenges into various themes and confirms those understanding with the participants. In addition, options to resolve the challenges are discussed with the participants during the second round of interviews. By conducting the interviews in two rounds, this research work is aligned with the DSR, which advocates iteration and participation (Teixeira et al., 2019; Dresch et al., 2014).

All the interview transcripts are sent to the participants for verification and confirmation. In addition to coding the names, gender-free terms, such as male pronouns are used regardless of gender. All other information, where names are not critical for analysis, is redacted by the organisation to maintain absolute confidentiality.

3.5. Summary

This chapter includes three main parts. It begins with discussions on the nature of business research, which is the search for information in a systematic approach to creating new knowledge. The creation of knowledge is emphasised as a critical outcome.

The second part of the chapter is the research framework, which defines the research philosophy and methodology as guided by the research onion proposed by Saunders et al. (2007). The research stages include philosophies, approaches, strategies, choices, time horizon, and techniques and procedures to collect and analyse data.

Finally, the chapter deliberates the role of insider-researcher and related ethics issues are to ensure that the research project maintains its objectivity, no harm, and confidentiality.

Chapter 4. Results and Discussions

4.1. Preamble

The chapter starts with a discussion of the case study organisation and a description of the data in Section 4.2. It is followed by the analysis of results in Section 4.3, where challenges encountered by the staff are discussed to draw insights. Section 4.4 draws insights from the literature review and critically assesses the ability to generalise findings from this project. Section 4.5 deliberates on the data analytics tools and recommends one that is the most suitable for ABC to implement a data-driven, contextual marketing strategy. Section 4.6 draws lessons learned from this research project to identify critical success factors, and section 4.7 describes the main constraints. Finally, Section 4.8 summarises the discussions and conclusions ofthe chapter.

4.2. Case Study Organisation and Data Description

4.2.1. General Background

The case study organisaion, ABC, is a small, professional body in Singapore. It is dedicated to the advancement and development of the profession, by advocating the interests of the profession, and developing their knowledge, skills, and expertise. Professional bodies are examples of not-for-profit organisations (Hess et al., 2019).

ABC is an affiliate to a global professional body, which shares the common commitment to advance the growth of the profession globally. ABC’s vision is to advance the profession to make them indispensable in its field of practice. This is to support the mission to lead the profession and advance their value to the organisation and stakeholders.

4.2.2. Strategic Goals

In its attempts to deliver its mission and vision, ABC has identified four strategic goals, which are to:

(1) Drive the development of high-performing professions to make them indispensable to their organisations and stakeholders.
(2) Deliver value that compels the professionals to join ABC as members.
(3) Raise the profile and demand of the profession.
(4) Operate as part of the global profession and organisation.

The two important strategic goals of ABC are to engage members and develop them professionally through training courses. Currently, the organisation uses a “one-size-fits-all” mass marketing strategy to promote its training courses, which account for the majority (75%) of its revenue. Financially, ABC has a small reserve, and due to the COVID-19 pandemic, many of its training courses were canceled, leading to a significant drop in revenue, which was insufficient to cover the expenses in 2020.

The losses incurred in 2020 due to the course cancellations have highlighted ABC’s reliance on delivering training courses to generate revenue. They have also emphasised the importance for ABC to improve its marketing and delivery of training courses. Therefore, ABC must engage its members better by sharpening its strategy through contextual marketing approaches backed by data analytics. This can be achieved by analysing the members’ profiles such as their working experience, seniority, and industry of their respective employers, to recommend suitable courses to them. This would reduce the number of “junk mails” that its members receive, which in turn, would lead its members to pay more attention to the marketing materials.

Due in part to a lack of expertise, and financial reserves, the management intends to start small, or to take “baby steps”, before the organisation gains more experience, confidence and knowledge to deploy data analytics widely throughout the organisation.

4.2.3. Organisational Structure and Project Team

ABC employs 11 full-time staff, led by the Executive Director, to run its day-to-day operations. The organisation is structured by functions in the following manner:

- Technical and Training
- Marketing and Communication
- Membership
- Special Project
- Office and Operation

As this research project on data analytics impacts all the areas except Office and Operation, staff in the Office and Operation function are not invited to participate in the interviews. The only Special Project staff is assigned as the project manager to lead the project for the organisation. The Executive Director, being the most senior staff, is the sponsor for the project.

4.3. Analysis of Data and Results

The analyses of this research project include:

(1) Ascertaining the organisation's business case to embark on the data analytics project. This is because one of the common causes for failure in data analytics projects is a lack of business case, which is critical to justify and communicate the benefits throughout the organisation to reduce resistance (Tamilarasu, 2012). The understanding of social systems facilitates better appreciation of the dynamic systems (Sterman, 2000), which in turn will develop better corrective actions (Forrester, 1995).
(2) Identifying common themes raised by participants during their interviews. The following steps suggested by SAGE Research Methods Datasets (2015) were performed:
    (d) Typing out the interview transcripts, which were sent to the participants for confirmation.
    (e) Reading the confirmed transcripts several times for analysing and identifying the initial codes.
    (f) Reviewing the initial codes to identify the common themes.

(3) Identifying the challenges, through reviewing the common themes noted in step (2) above, to implement data analytics strategies; and
(4) Comparing the challenges raised by the staff and management against those noted in the literature (as detailed in Chapter 2 Literature review).

The above analyses answered the research question:

- What are the challenges and constraints to implementing data analytics strategies in small, not-for-profit organisations in Singapore?

Simultaneously, the following research aim and objective are addressed:

- Research aim - Identify challenges and constraints to implement data analytics strategies in small, not-for-profit organisations.

- Research objective - Analyse key challenges to implementing data analytics strategies confronting the not-for-profit organisation, in Singapore, with limited resources and know-how, through interviews and review of archival records.

4.3.1. Business Case

As discussed above, the first step of the analysis is to ascertain the organisation's business case to embark on the data analytics project. Tamilarasu (2012) highlighted that a business case is critical to justify and communicate the benefits to reduce resistance.

4.3.1.1. SWOT Analysis

Before the idea was formed to implement a data analytics strategy, ABC, under the leadership of the Executive Director, performed a SWOT analysis, which is part of the archival documents reviewed for this research project to understand the strengths, weaknesses, opportunities, and threats of the organisation. The conclusions of the SWOT analysis include the need to strengthen its marketing capability to promote its training courses, which is aligned with the aims of this research project.

<u>Strengths</u>

As ABC is an affiliate to a global professional body, it can tap on the global resources to train its members. It is having a niche market serving a particular profession in Singapore. Members in the profession are required to attend a minimum number of training hours, known as continuing professional education (CPE), per year. ABC is in the position to conduct courses to fulfill the training needs of the professional members. ABC has also maintained excellent collaborative working relationships with stakeholders, such as regulators and its peers in other countries.

<u>Weaknesses</u>

The key weakness starts with its weak financial position, as the collection from membership fees is not adequate to pay its operating expenses, which include staff costs, office rental, and other administrative expenses. ABC relies mainly on training courses and seminars to generate revenue to sustain its operations.

Due to limited financial constraints, ABC makes very minimal investment in the membership management system, which has limited capabilities to record its membership information for effective engagement. This in turn leads to inadequate understanding of the members' needs to serve them effectively.

ABC acknowledges that certain segments of its members are underserved. Furthermore, memberships have very low growth rate in the last five years. The management sees the need to enhance its membership management system and engage its members better.

Opportunities

The profession served by ABC is identified as one of the high growth practice areas in the Committee on the Future Economy report, sponsored by the Singapore government. This means that the government is willing to train more Singaporeans to take up jobs in the profession, giving rise to training demand.

It is also a requirement for the profession to undertake CPE hours to keep abreast of the latest developments in the profession. As every member must gain at least 40 CPE hours annually, the demands for training are great opportunities for ABC to enlarge its revenue sources. ABC has found that there are gaps between the supply and demand for training needs, especially for members working in certain industries.

Threats

The biggest threat for ABC is the availability of other training institutions, commercial providers, or professional bodies who can organise similar training courses or seminars to compete with ABC. If these competitors are successful, ABC may lose market share as its members would be attending courses organised by the competitors instead of those by ABC. The situation, if materialised, would be dire for ABC as it would lose its main revenue sources.

The key strengths, weaknesses, opportunities, and threats from the SWOT analysis are summarised in Table 4.1 below.

Strengths	Weaknesses
• Strong capabilities to conduct training courses	• Weak financial positions • Lack members management system

	• Inadequate understanding of members profile
<u>Opportunities</u> • Niche market as members must attend continuous professional training • The growing area identified by the Singapore government, who provides fundings to train mid-career Singaporeans	<u>Threats</u> • Competitions from other service providers • Online courses which can become a substitution

Table 4.1: Summary of SWOT Analysis by ABC

<u>Communications of SWOT Analysis</u>

All the staff were involved in the SWOT analysis, which was led by the most senior person, Executive Director. As a result of this wide participation within the organisation, the SWOT analysis is widely accepted because there is a sense of ownership. In addition, the outcomes of the SWOT analysis are communicated to the Board of Governors, the highest supervisory board of ABC. Hence, the conclusions of the SWOT analysis were communicated to all levels of the organisation.

4.3.1.2. Balanced ScoreCard (BCS)

With the results of the SWOT analysis, ABC has adopted the balanced scorecard approach to set organisations targets in terms of financial, customer, internal process, and learning and growth.

For ABC to achieve financial sustainability, which means its revenue must be higher than its expenses, ABC must engage its customers/members better to promote training courses that account for more than 70% of its revenue. By adopting a data-driven, contextual marketing strategy, ABC can engage its members more effectively as the marketing effort is based on the understanding of the members' needs. This will lead to a higher probability that members would sign up to attend the courses.

In summary, ABC has a strong business case to launch a data-driven, contextual marketing strategy. The need to do so is well understood by the staff, as most of them worked with their leader to perform the SWOT analysis.

4.3.2. Challenges Encountered by the Staff Members

As discussed in the Methodology chapter, the interview is the main data collection method adopted for this research project. One of the research questions is to identify the challenges and constraints that the small, not-for-profit organisation would encounter when it implements data analytics strategies. Therefore, the interview questions have been designed to enquire the participants about the challenges they envisaged. As the participants are the subject matter experts of the processes and daily operations, their views are valuable input for the research project.

The interviews conducted by the research students are transcripted for analysis. The following steps, which are recommended by SAGE Research Methods Datasets (2015), are adopted to identify themes raised by the interview participants:

- Identify initial themes based on challenges noted in the literature review.
- Read the transcripts to identify initial codes.
- Write and review codes for revision.
- Identify themes, which are a combination of those noted in the literature review and those raised by participants.

Based on the literature review, the initial list of challenges is:

- Leadership
- Talent management
- Funding availability
- Organisation culture
- Data management

The semi-structured interview questions, which have been approved by the UON Ethics Committee, are attached in Appendix 1.

After analysing the interview transcripts, it is noted that the participants have raised challenges that can be attributed to the following five themes:

- Leadership
- Organisation culture
- Skill shortage
- Funding
- Data management and availability

In the table below, tick (√) means the participants have expressed positive comments towards the topics while a cross (X) means the participants have expressed concerns. For example, four participants (Participants 2, 5, 7, and 8) have spoken about leadership and all of them expressed confidence that the organisation leaders will support the project.

This is summarised in the table below and elaborated in the subsequent section.

Table 4.2: Positive comments (√) or concerns (X) expressed by the participants.

	Participant								
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Leadership		√			√		√	√	
Organisation culture - **Awareness that changes are essential** - **Resistance to changes**	√	√	X	√			√	√	√
Skill		X	X	X	X		√	√	√
Funding	X		X	X			√		√
Data management	X	X	X	X	X	X	X	X	X

Legend:

√ - Positive comment
X - Concern

The second round of interviews was conducted with all the participants to confirm the challenges identified through the analysis of interview transcripts by the research student. As one of the participants has left the organisation, there were eight interviews held in the second round, as compared to nine in the first round. This brings the total number of interviews to 17, slightly above the minimum of 15 interviews recommended for generalisation findings in single case studies (Marshall et al., 2013).

As the second interviews were held to confirm the understandings with the participants, they also serve as triangulation, as described in Chapter 3.

4.3.2.1. Leadership

<u>Perceived support levels from the leaders</u>

As argued by many authors (Gartner, 2018; McAfee and Brynjolfsson, 2012; Ransbotham et al., 2016), leadership plays an important role in the success or failure to implement data analytics strategies.

The importance of leadership is agreed upon by four of the interviewees. For example, participant 2 said: "There is this common saying of walk the talk and tone from the talk. So top management's buy-in has to be filtered down to all levels across the set-up of the organisation. The right message that such an initiative has values and benefits to individuals and the organisation as a whole." In addition, Participant 9 said: "The project needs to be driven at a high level…"

The participants have also noticeably expressed their confidence in their organisation leaders. As Participant 7 said: "The board is very supportive and are very aware that we need to move on. We need to be at the forefront, especially with the uncertainty because of COVID-19, the mindsets are all changed." He further said that: "The tone from the top is not a concern."

The participants opined that leaderships are an important ingredient for the success of data analytics strategies, similar to observations noted in the literature review. They are confident that the leaders in ABC are mindful that digitalisation and data analytics strategies are critical to the organisation's survival, hence, support from the top is not a concern. As Participant 2 has said: "This is not just smart business. It's essential for survival." Participant 7 further said that "Everybody wants to progress, everybody says how can we do better, how can we do it more effectively."

During the second interview, all participants affirmed that leadership supports are important, and they are not lacking in ABC. One participant emphasised that support from the top is "not only important but essential".

4.3.2.2. Organisation Culture

<u>Perceived awareness levels of digitalisation and data analytics</u>

In ABC, most of the participants, regardless of their ranks in the organisation, are aware that digitalisation and data analytics is important for the organisation to survive. As Participant 7 has put it: "Data analytics is so important to us now in understanding our memberships", and "it is not a choice anymore.", while Participant 8 said: "In this modern-day and age, we have no choice but to do so", and Participant 9 said: "many businesses realised that they have to transform digitally and adopt technology in whatever they do".

The widespread understanding of the importance of data analytics noted in ABC is contrasting to the views put forth by Microsoft and ASME (2018), who argued that in Singapore, the SMEs owners or key decision-makers have limited knowledge about the benefits of digitalisation resulting in slow adoption of data analytics strategies in the country. The observations in ABC are also contrasting to those noted by Ogbuokiri et al., (2015), who argued that there was a lack of awareness, among the SMEs in Singapore, about data analytic strategies.

<u>Resistance to Changes</u>

While implementing data analytics strategies, employee resistance and organisation culture could de-rail the plan (Microsoft and ASME 2018), therefore, widespread culture change is required and organisations are encouraged to make the changes in stages (Shivkumar, 2019).

Although resistance to changes has caused failures in many projects (Griffith-Cooper and King, 2007), there is little evidence of resistance noted in ABC. All the participants acknowledged that it is necessary to embrace changes to implement data analytics. This could be attributable to the open communication in ABC as the staff was involved in the SWOT analysis. The involvement has given them a sense of ownership and promotes acceptance of changes. This demonstrates that clear communication reduces employee resistance (Andersen, 2012; Muller and Turner, 2010).

Most of the participants do not foresee culture to be a stumbling block for ABC to launch data analytics strategies. Participant 9 said: “that (culture) should not be a significant challenge for us. Our organisation is very small, and therefore, the team generally has to work closely together.” And Participant 4 added: “I think so far it (collaboration culture) is OK, with the recent experience of CRM migration, we try to adapt to the new changes, just that different people have different learning speeds.” This is advocated by Participant 7, who said: “After going through these few months when we have to migrate our data and have to learn the new system, the mindset is about right now.” and “data analytics is just another part of the journey. I think they are ready. If you asked me about three years ago, I would be very hesitating, but as of now, we are very used to changes.”

The above suggests that ABC has prepared its staff to adapt to changes. However, there is one participant who suggested that the collaborative culture in ABC may not be ideal, as Participant 3 said: “I am not sure whether I am right, we are quite departmentalised, one is event handling, then training, and membership.” Therefore, to avoid the pitfall of departmentalise and self-interest, the project's purposes must be properly explained. This is also emphasised by Participant 9, who said: “If you talk about the people, attitude, and culture, the starting point must be to get everyone on board, to agree on the purpose of this project, the benefits we expect to see, and how it would help our organisation in the long run.”

In the second interview, all participants affirmed that culture is not a stumbling block for ABC to successfully implement a data analytics strategy. They agreed that with clear communication, “departmentalisation” is not a big issue in ABC. While confirming that communications among the staff are generally good in ABC, Participant 1 added that staff may not fully understand the data requirements of other departments, hence not all the requirements are incorporated in the systems.

4.3.2.3. Talents/training

<u>Perceived level of skill shortages</u>

It was cited that the slow adoption rates of data analytics and digitalisation among the SMEs are due to the lack of talents with IT skills (Microsoft and ASME, 2018; Gartner, 2018; Coleman, 2016), statistical skills (Coleman, 2016), managerial skills and human capital (Shivkumar, 2019; OECD, 2018; OECD, 2017). Talent shortage (Segarra et al, 2016; Fadairo and Maggio, 2015; McAfee and Brynjolfsson, 2012) and lack of internal experience (Ransbotham et al., 2016) are critical roadblocks to develop and implement data analytics strategies.

In this research project, seven interviewees named skill shortage as one of the obstacles to launch data analytics strategies and expressed a need to strengthen the skillsets of the existing workforce. As Participant 3 said: "The size of each department is not big, so to go deeper to develop contextual marketing would need more skillset." and Participant 4 added: "In terms of data analytics, I only have experience with Excel. Not sure about other tools. And for Excel, it is used mostly with functions like pivot table to help with data analytics." Participant 8 agreed that skill shortage is a challenge as he said: "We need people to reskill." The quotes demonstrate that data analytics skills are lacking and confirmed with the views noted in the literature review.

During the second interview, all participants acknowledged that the staff is not familiar with data analytics tools. Participants 2 highlighted that the organisation has never implemented data analytics strategies and hence, there was no need for staff to pick up the skills. However, when the needs arise, the participant is confident that the staff will pick up the new skills.

<u>Confident levels to solve skill shortages</u>

While skills are lacking, the participants generally are confident that skill shortages can be overcome. For example, Participant 7 said: "if we can take baby steps, we can take internal resources and train the person. Let the person acquire the competencies as we move along." and the view is supported by Participant 8, who said: "Our existing marketing staff may not be adequately exposed or equipped to do this, but they will over time." Therefore, the staff is generally optimistic and confident that with proper training and appropriate pace of development, they can pick up the necessary skills to implement data analytics strategies successfully.

Furthermore, the costs for training could be reduced due to the familiarity of the market, as Participant 7 has said: "We can look at some of the programs that are offered, we are a profession, we are helping our members to upgrade their data analytics skills. Because of that, we are aware of very credible vendors, who work jointly with the Institute of Higher Learning (IHL) to offer data analytics courses. Hence, to upskill and to attend courses are not very expensive. It is just that a lot of time is involved. So, I think it is very possible."

The above views expressed by Participant 7 contrast with those of McAfee and Brynjolfsson (2012), who argued that the lack of awareness in digitalisation and data analytics has led to the perception that data analytics strategies are expensive to implement.

To sum up, the participants generally opined that there are skill shortages in ABC. These opinions are aligned with the views noted in the literature review. However, contrasting to those noted in the literature review, ABC does not perceive training costs to be high.

During the second interview, all participants expressed confidence that they can pick up the data analytics skills, especially if the tools chosen are not complex. Participant 8 emphasised that data analytics strategy does not require complex tools. He has suggested that the functions in Microsoft Excel may be sufficient to serve the needs of ABC.

4.3.2.4. Funding

<u>Perceived level of funding shortages</u>

Funding and cost issues are closely related to the talent shortage problems, as the implementation of data analytics strategies is intensified by the excessive hiring costs for people who master data analytics skills (Fadairo and Maggio, 2015). In Singapore, many SMEs perceived data analytics strategies require high investment costs (Microsoft and ASME, 2018; Ogbuokiri et al., 2015).

In ABC, while six of the participants have spoken about funding as an issue, most of them opined that it can be resolved and should not pose a challenge to launch data analytics strategies. As Participant 9 has said: "Definitely, it will require a significant investment of resources", "funding includes the upgrading of systems", and "to progress with time, or to remain relevant in how businesses operate in today's landscape, it is something we have to work towards. That is one important reason to do it. We have to find other ways to look at funding issues."

The quotes by Participant 9 illustrate that when organisations acknowledge the importance of data analytics, they will find ways to resolve the funding issues.

In the current environment, cost pressure has become a lesser issue as technology has advanced to reduce the costs, especially with the availability of open-source applications, such as Hadoop (McAfee and Brynjolfsson 2012; Segarra et al., 2016).

During the second interview, the participants acknowledged that the organisation has limited funds, however, they do not expect large investments to implement the data analytics strategy. Participant 8 highlighted that it is a general misconception that organisations associate data analytics strategies with huge investments.

4.3.2.5. Poor Data Management

Many big organisations are struggling to ensure that their data achieve a certain quality standard, and the problems become more acute when the data volume is huge (Cheng et al., 2015; Ransbotham et al., 2016). However, there is little mention that the same challenges also exist in small organisations, especially those with small data volumes.

The interviews conducted by the research student reveal that data quality issues also exist in ABC, a small organisation with a small data volume. All the participants expressed concern that the existing data quality may not be adequate for the project. Participant 5 has started it as he said: "The data quality is the main factor contributing to whether the contextual marketing strategy is effective or not." and "The data collection is a challenge". Along the same line, Participant 9 said: "The first thing is the data collection part, which is an important starting point…. The other challenge is whether our current infrastructure or system allows it. To build up such a database, we would need to ensure that our system can capture this information and from there, we would be able to mine the information."

Participant 7 has analysed the situations and provided insight into the root causes of the data issues, as he said: "We have a lot of legacy data, and we rely a lot on Excel, the systems that we have were not able to produce the information, or the data, or export the data for our analysis."

Similarly, Participant 4 added: “Previously, our system does not support this. The data that we collected from the members was only about their employers, designations. We don’t have information about courses that they attend. The information may be available, but we were using Excel to record registration, attendance, which are done manually.”

While the above quotes suggest that information was not available to perform data analytics, the situation has improved. Participant 4 continued: “Now, with the new system, we use it to record registrations for courses and events, members register on the system, so now they are being recorded digitally. In terms of the member profile data, when they sign up for the account, they are required to fill in details about themselves, so we can get more information about their demographic. We just started with the system, so maybe over time we can get more data, like what kind of training topics they prefer, and what kind of topics they attended.”

Agreeing with Participant 4 that the situation is improving, Participant 7 said: “Data is never ready because we have been in existence for 40 over years. What we can do is act up to a certain stage when it stabilises. I would think it is about half a year before we can look into the data and trying to make sense out of the data.” This suggests that while the situation is improving, the organisation needs at least another six months before the data can be ready to launch the data analytics strategies.

However, the duration to get the data ready is an estimate. Different individuals may estimate it differently. As Participant 7 estimates it to be at least six months, Participant 8 is more conservative by saying: “It is probably an evolution, rather than a direct cut-off that if I do something and overnight the data is where it is supposed to be. I reckon that it is going to be a 2 to 3 years journey.”

In the second interview, the participants unanimously agreed that data availability is the biggest challenge for the organisation to launch a data analytics strategy. One of them has added that about 30% of the membership fees are paid by their organisation, hence, these members may not log on to the membership database to update their profiles. As a result, their information will not be available for data analytics.

4.4. Critical Discussions

This research project attempts to fill the research gaps noted in the literature review by focusing on the implementation of data analytics strategies for small, not-for-profit organisations. Therefore, the critical discussions start by comparing and contrasting the research findings against those noted in the literature review.

Next, as the research project has adopted the case study approach using one small organisation to go in-depth in the research, the number of interviews is considered small. Therefore the critical discussions will also address the ability to generalise the findings.

4.4.1. Compare and Contrast Against Literature Review

As mentioned above, this research project was initiated because of the research gaps noted in the literature review, as discussed in chapter 2, the discussions start with comparing and contrasting the findings in this research project against those noted in the literature review.

Table 4.3 below compares and contrasts the challenges noted in the literature review (i.e., those confronting big organisations, and SMEs) against those noted in ABC, the case study organisation. The noticeable differences are the attitudes towards leadership, talent shortages, and funding:

- While leaderships are raised as a challenge in the literature review for both big organisations and SMEs, it is not a concern for ABC as all the staff is confident with the support from the top.
- While talent shortages are big challenges in big organisations and SMEs, ABC is very confident to overcome the issue by training the staff without incurring high expenses.
- Like many SMEs, ABC has limited funding. However, unlike many SMEs who quoted the lack of funding to be a stumbling block to implement data analytics strategy, ABC opined that the data analytics strategies are so important that the organisation must find the fund to implement.

Organisation culture and resistance to change are other big challenges noted in the literature reviews but they are not perceived as a challenge for ABC.

Literature review did not cite data management as an acute problem for SMEs, however, it is the most cited challenge in ABC. The implementation of the data analytics strategy cannot be completed in ABC because of a lack of data. It needs at least another six to twelve months to collect the data to be ready for the first analysis.

	Base on the literature review		**Based on interview**
	Big organisation	**SME**	**Case study organisation (ABC)**
Leadership	X	X	√
Org culture/ resistance to change	X	X	√
Talent/training	X	X	≠ (with training)
Funding	√	X	≠
Data management	X	√	X
Legend √ - Not a concern X – a concern ≠ - concern can be overcome			

Table 4.3: Compares and contrasts the challenges between those highlighted in the literature review and the case study organisation

4.4.2. Generalisability of Research Findings

This research project is adopting the case study approach, using one small, not-for-profit organisation, who employs less than 11 employees, in Singapore for in-depth understanding. Due to the small staff strength, random sampling is not possible for this research project. Therefore, the purposive sampling method is adopted.

It is expected that the ability to generalise the findings in this research project can be questioned in two aspects:

1) Can findings from research, which use one case study organisation, be generalised?
2) Can findings based on a small sample size be generalised?

Regarding the first question, it is a common criticism to generalise research conclusions based on findings from one case study (Singh, 2014, Marrelli, 2007, Tellis, 1997). To counter such criticism, the starting point is the definition of a case study, which is "an intensive study of a single unit to understand a larger class of similar units" (Gerring, 2004, pp 342).

It is argued that samples may be selected from a single organisation (Marrelli, 2007; Tellis, 1997), location, person, or event (Bryman and Bell, 2011), to gain an understanding of a larger class. Furthermore, high-quality findings from case studies can be generalised (Noor, 2008; Lee et al., 2007; Gerring, 2004). The case study is intended to focus on a unit of analysis or a specific issue, and the understanding can be particularly useful to enable generalisation (Noor, 2008).

On the second question regarding the ability to generalise conclusions obtained from a small sample size, the starting point is the definition of a small sample, which is defined as those smaller than 30 (Beuckelaer and Wagner, 2012).

It is noted that research conclusions based on a small sample can be generalised as long as the findings are valid (Baskerville and Wood-Harper, 1996), although the manner it is generalised may differ from those based on a random sample (Hood, 2006). In this research project, due to the small staff strength, random sampling is not possible, instead, the purposive sampling method, which is recommended by Kerr et al. (2010), Marrelli (2007), and Hood (2006) is adopted.

Findings can be generalised with 15 to 30 interviews in single case studies (Marshall et al., 2013), and with 2 to 3 interviews per person (Morse, 2000). In this research work, 17 interviews were conducted with 9 different participants. Eight of the participants were interviewed twice and one participant was interviewed once because he has left the organisation when the second interviews were planned.

4.5. Implementation

4.5.1. Project team structure

The implementation starts with defining the purposes and objectives of the project. As noted in the SWOT analysis performed by the staff, ABC needs to strengthen its marketing capability to attract more members to attend its training courses. The outcomes of the SWOT analysis are shared with the staff who agree that ABC needs to strengthen its strategy.

This research project aims to identify the challenges to implementing the data-driven, contextual marketing strategy for ABC. In short, the SWOT analysis defines the "what" needs to be done while this research project establishes the "how" to do. The most senior person, who is the sponsor for the project, takes ownership to explain the purposes of the data analytics project to the staff. The project manager is also appointed to lead the change project to implement the strategies.

The establishment of the project purposes, formation of the project team, and appointment of a project manager have set the platform for ABC to launch its data analytics, contextual marketing strategy. This helps to make sure that the content, people, and process are aligned, as proposed by Al-Haddad and Kotnour (2015).

In the subsequent sections, the research project will discuss the plan to map relevant training courses to members.

4.5.2. Mapping Training Courses to Members

The contextual marketing strategy for ABC is to recommend suitable training courses to its members based on their profiles. Therefore, there are two items, namely the training courses and the members' profiles, that need to be analysed, coded, and mapped.

4.5.2.1. Understand Types of Training

In the design of training courses, ABC uses the profession's competency framework (Skillsfuture, 2020), where skills are classified into three categories:

(1) Technical expertise
   a. Business acumen
   b. Business innovation and improvement
   c. Process analyses
   d. Cybersecurity

(2) Attributes
   a. Independence
   b. Due professional care

(3) Soft skills

a. Leadership
b. Decision making
c. Interpersonal

In each of the categories, there are three skill levels:

(1) Basic
(2) Intermediate
(3) Advance

For coding purposes, “basic” is coded as “1”, “intermediate” as “2”, and “advance” as “3”. Members with different seniorities have to determine the types of skills and the expected level of mastery they need. For example, a junior profession would require a “basic” level while the head of the department would require “advanced” level competence for business acumen. Table 4.4 illustrates the competence levels for technical, attributes, and soft skills for the profession depending on their roles or seniorities.

Type	**Competence**	**Seniority of Profession**			
		Junior Profession	**Assistant Manager**	**Manager**	**Head of Department**
Technical	Business acumen	1	2	2.5	3
Technical	Business innovation and improvement	1	1	2	2.5
Technical	Process analyses	1	2	2.5	3
Technical	Cyber security	1	2	2	2
Technical	Data analytics	2	2	2.5	2.5
Technical	Digital technology environment scanning	NA	1	2	2.5

Attributes	Due professional care	1	1	2	2
Attributes	Independence	1	2	2.5	3
Technical	Enterpise Risk Management	1	2	2.5	3
Technical	Financial Statement analyses	1	1	1	1
Technical	Fraud risk management	2	2	2.5	3
Technical	Governance	NA	2	2.5	3
Soft skill	Leadership	NA	NA	2	3
Soft skill	Decision making	NA	NA	2	3
Soft skill	Interpersonal skills	2	2	3	3
Soft skill	Developing people	NA	NA	3	3
Soft skill	Communication	1	2	2	3
Soft skill	Problem-solving	NA	2	NA	NA
Soft skill	Teamwork	1	2	NA	NA
Technical	Digital literacy	2	3	NA	NA

Table 4.4: Training types and the expected mastery level for the profession

Source: Adapted from Skillsfuture (2020)

With the above, the courses are coded with the following information:

- Type – e.g., technical, attribute, and soft skill.
- Competence - e.g., business acumen, innovation, and improvement, etc.

- Seniority – e.g., 1 (for basic), 2 (for intermediate) and 3 (for advance).

Table 4.5 below summarise the coding applicable for courses.

Type	Competence	Seniority
Technical	• business acumen • business innovation and improvement • cybersecurity • data analytics • digital technology and environment • enterprise risk management • fraud risk management • financial statement analyses • governance • digital literacy,	1, 2 or 3
Attribute	• due professional care • independence	1, 2 or 3
Softskill	• leadership, decision making • interpersonal skill • developing people • communication, problem-solving • teamwork	1, 2 or 3

Table 4.5: Coding for courses offered

4.5.2.2. Understand Members' Database

After coding the training courses, the members' profiles should be analysed and coded. This section discusses the members' information required to map them to suitable courses. This will address the research objective: "Identify the required information in the member's database that is required to devise segmentation and contextual marketing strategies"

As recommended in the last section, ABC codes its courses according to technical, competence, and seniority. Correspondingly, the member profiles should include the members' roles or seniorities. Members can do so by indicating that they are "junior profession", "assistant manager", "manager" or "head of the department". By doing so, they can be mapped to the training courses that match their skill requirements.

For example, if a member is a "junior professional", he will be recommended to attend courses that are coded as "basic", while a "head of the department" will be recommended to attend courses that are coded as "advanced". In this way, "junior professional" would not receive marketing materials for "advanced' as they are not suitable, therefore, members are receiving marketing materials that are catered to their roles and seniority.

4.5.3. Shortlist Data Analytics Tools

This section discusses the data analytics tools available for ABC, the pros and cons of the tools, and the reason for choosing a particular tool for ABC. These will address the research objective: "Recommend suitable data analytics tools to implement data-driven, contextual marketing strategies for the small, not-for-profit organisation, bearing in mind the challenges and constraints confronting the organisation."

There are many tools, such as Python, SQL, R, and Microsoft Excel, which ABC can select to map the members' profiles to the courses. In shortlisting the suitable tools, considerations are given to the capability of the tools as well as the knowledge of the staff. Python, SQL, and R are advanced data analytics tools that are suitable for data beyond 10 megabytes. Microsoft Excel provides very basic data analytics, such as simple mapping, and it is suitable for small data, typically less than 10 megabytes.

Given that there is a small member base (less than 3,000), the file size is less than 10 megabytes, the research student opines that Excel can satisfy the needs for ABC, and proposes it as the preferred option among the data analytics tools. This is also aligned with the views from Participant 8, who suggested during the second interview that the functions in Microsoft Excel are sufficient for ABC's needs.

4.5.4. Data Analytics Tools

As discussed in the previous section, the research student explores various data analytics tools, such as Python, SQL, R, and Excel, where the latest is recommended. DSR approach is adopted for this research project, where iteration is advocated to develop solutions to solve real-world problems (Heathcote et al., 2020; Teixeira et al., 2019). Therefore, the research student discussed the proposal with the participants during the second round of interviews.

During the first round of interviews, participants said they do not have knowledge beyond Microsoft Excel, and they prefer to take “baby steps” in their journey to learn more about data analytics. During the second interview, Participant 2 clarified that the staff is not trained in data analytics tools “because there is no such need” and “it is different when the need arises”. This demonstrates that there is a willingness to pick up new skills.

Data analytics tools have evolved over the last few decades, with one breakthrough that happened recently where big data like Hadoop and distributed computation like Spark, allow huge data storage and computation to be performed in small mass computers that are much cheaper than super computers. In addition, Google Brain has been developed using Python and allows non-coders to master “deep learning” coding. All these developments have made data analytics cheaper.

Although Python, SQL, and R are more advanced, they are more complex than Excel. Being new to data analytics, the staff are more comfortable and confident to handle something they are more familiar with, compared to tools that are advanced but complex. In addition, the participants expressed their preferences to start with simpler tools. During the second interview, participant 8 mentioned that “a lot of people think that we need to have sexy, complicated tools but we can use Excel to perform simple data analytics.”

The simplicity of Microsoft Excel allows the staff to learn basic data analytics and gain confidence. By starting with a tool that staff is familiar with and confident is aligned with the recommendations to break data transformation projects into manageable chunks (Shivkumar, 2019; Alibaba Cloud, 2018; Bump, 2015; DBS, 2014; McAfee and Brynjolfsson, 2012). With the participants generally expressed their preferences to use simpler tools during the second round of interviews, Excel is recommended as there are wide acceptances among the participants. The selection of a widely accepted tool is being human-centric, as advocated by DSR.

However, due to the lack of members’ data, the mapping tool developed using Microsoft Eexcl could not be used to test the solutions. This is a limitation to this research project, however, with more time and data could be collected, the solutions can be tested in due course.

4.6. Lessons Learnt – Critical Success Factors

ABC has made a successful first step to implement the data analytics, contextual marketing strategy. Although the journey is ongoing, there are many lessons learnt that can be drawn from the experiences. Factors that are contributing towards the success of ABC include a clear business case, strong leadership supports, a changing culture, a well-defined communication plan, exposure to the latest developments, and structured project governance. On the other hand, it faces constraints, such as lack of data availability, and resources.

Figure 4.1 below summarises the success factors at ABC.

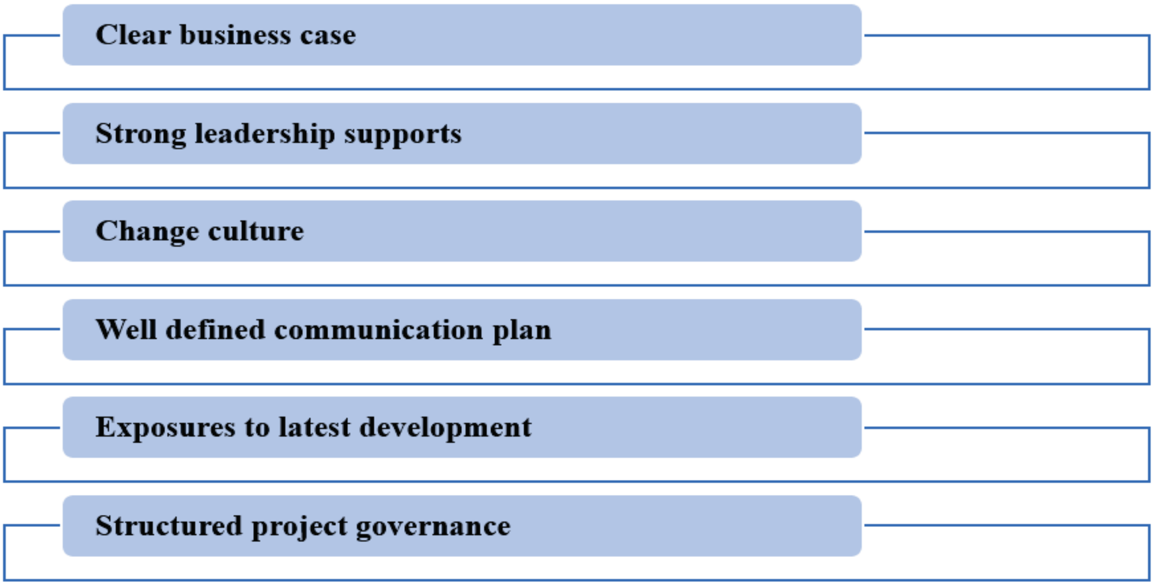


Figure 4.1: Lesson learnt: ABC's success factors in launching data analytics strategy

One of the research objectives in this research project is to perform reflection to identify learning experiences and make recommendations for small, not-for-profit organisations to implement data analytics strategies successfully. This section discusses the success factors and roadblocks in greater detail before making recommendations.

The lesson learnt, derived through reflection, can be added to the body of knowledge for sharing with academics and practitioners. Academics can use them as a foundation for further research, while practitioners can use them to launch data analytics strategies.

4.6.1. Clear Business Case

Change management projects, including a change in marketing strategy, must start with a clear purpose, which must be articulated by the project owner (Andersen, 2012). As a start, ABC has performed a thorough SWOT analysis to identify its strengths, weaknesses, opportunities, and threats. From the analysis, ABC found opportunities to expand its training courses to generate more revenue. It has also found weaknesses to engage its members (main customers) effectively, resulting in limited success in promoting its courses.

Through the SWOT analysis, the management recognises that there is a need to strengthen its marketing strategies to engage its members more effectively to promote the training courses. Therefore, there is a clear purpose to adopt a contextual marketing strategy, which requires data analytics to analyse the members' profiles and match them to appropriate courses. In summary, ABC has a clear business case to articulate that it needs to embark on changes.

4.6.2. Strong Leadership Supports

Digital transformation is tantamount to business transformation, and top management support is one of the most important ingredients for data analytics strategy to be successfully implemented (Alibaba Cloud, 2018). Therefore, the success of the project boils down to leadership supports.

When ABC performed the SWOT analysis, there was clear leadership as the exercise was led by the most senior staff. As staff participation and their input were considered in the SWOT analysis, there is a strong sense of ownership throughout the hierarchy. Collectively, the team agrees that ABC must strengthen its financial positions, and the most feasible solution is to increase its revenue from training courses.

The leadership supports extend to the organisation's Board of Governance. This is confirmed during the semi-structured interviews where participants opined that support from the top is not lacking. This is aligned with the observations made by the research student, who also notices comradeship and great team spirit within the organisation.

With the strong support from the top, coupled with the strong team spirit in the organisation, ABC has a strong foundation to implement a new data-driven, contextual marketing strategy.

4.6.3. Change Culture

Organisation culture and employee resistance could de-rail the data analytics implementation plan (Microsoft and ASME 2018), therefore, organisation culture must be catered to embrace changes (Shivkumar, 2019). In addition, organisations are encouraged to make the changes in stages (Shivkumar, 2019; Alibaba and Cloud, 2018; Bump, 2015; McAfee and Brynjolfsson, 2012).

ABC has created an environment where the staff understands that the organisation needs to change to move forward. Supported with a clear purpose to change, top management's direction, and clear communication, the staff are receptive to embrace data analytics to strengthen their strategies. During the structured interviews, many of them have stated that there is no choice but to change. This demonstrates the change culture in the organisation.

ABC has decided to take "baby steps" in the implementation of data analytics strategies. It has decided to pilot data analytics for the marketing of courses. This approach is aligned with the recommendations by Shivkumar (2019), Alibaba and Cloud (2018), Bump (2015), and McAfee and Brynjolfsson (2012) to implement changes in stages.

The pilot approach has also provided staff to be trained, while the new strategy is being implemented on small scale. It would allow staff to see the improvements made to their work and other benefits, hence increases the chances for success. This implementation strategy is to give priority to data analytics to departments who could benefit most from the initiatives in the shortest timeframe, which would help to create momentum for the organisation (Alibaba and Cloud, 2018; Bump, 2015).

4.6.4. Well Defined Communication Plan

Not communicating the vision adequately and not articulating the need to change are two of the main causes for failures in change management projects (Griffith-Cooper and King, 2007). Therefore, communication is the cornerstone of successful change management (Al-Haddad and Kotnour, 2015; Lam, 2009; Griffith-Cooper and King, 2007).

ABC has communicated the need to change clearly to all the staff, who understand the importance. During the semi-structured interviews, a few participants emphasised that "it is not a choice" but the organisation must change and embrace digitalisation to survive.

ABC has differentiated itself from the other Singapore SMEs, who lack the awareness of data analytics (Microsoft and ASME, 2018; Ogbuokiri et al. 2015). In ABC, the staff is not only aware of data analytics, but they are strong advocates of their organisation embracing data analytics. With the support from staff, there is little resistance to change in ABC.

4.6.5. Exposures to Latest Development

ABC regularly organise seminars, where digitalisation, data analytics, and associated benefits are presented to its members. Its staff, who helped to organise the seminar, are exposed to discussion relating to the latest developments, such as digitalisation, and data analytics, amongst others. During the interviews, a few staff have emphasised that organisations may not survive the competitions if they do not embrace changes. This understanding has reduced staff resistance, which is commonly quoted as a cause for failures to implement data analytics projects (Microsoft and ASME, 2018; Wills, 2014).

4.6.6. Structured Project Governance

Clear communication, which can be done effectively through a simplified governance structure, to stakeholders is critical to garner their acceptance and support (Lam, 2009). The governance structure includes clearly defined roles and responsibilities of the project team and objectives of the project. ABC has set up a project team where the sponsor is the most senior staff. ABC has also appointed a project manager to coordinate the activities and oversees the project.

The ABC staff have also revealed that the organisation has embarked on a few change projects, such as membership system upgrades, in the last few years. With those experiences, the roles of the project manager are refined for greater clarity. This strengthens the execution of the data analytics project.

4.7. Lessons Learnt - Main Constraints

It is noted that ABC faces two main constraints, namely the availability of data and resources. In this research project, various options are explored, and recommendations are made to bring the project forward. The resolutions are worthy for the body of knowledge as other similar organisations can learn from the experiences. Figure 4.2 below summarises the two main constraints, which are discussed in the subsequent two sub-sections.

Figure 4.2: Main constraints faced by ABC

4.7.1. Data Management and Availability

In big organisations, the challenges for data management are caused by their huge volume and high velocity of creation (Ransbotham et al., 2016; Segarra et al., 2016; Cheng et al., 2015). ABC does not have the issue of huge data volume that is created at high velocity. In contrast, it faces data issues at the other extreme - a lack of data. ABC did not have a centralised system to capture its members' information. Some members' information available is recorded in a fragmented manner – in various spreadsheets and there is no systematic process to update the information regularly. This makes data analytics extremely difficult, if not impossible.

In mid-2020, ABC upgraded its membership database to capture its members' information centrally. However, it will take at least a year for members to update their profiles before data analytics can be performed. This is a constraint brought up by a few participants during the semi-structured interviews.

Drawing lessons learnt from the above, the availability of data is a prelude to data analytics. Small, not-for-profit organisations must invest in systems that can capture updated, and essential information before meaningful data analytics can be performed. The system may require a certain amount of investment, which brings us to the constraints regarding resources.

While data quality is important, organisations must be cognisant that the “perfect” data may not exist. Organisations must make a judgement call when the levels of data quality are adequate for them to perform data analytics to obtain reasonable assurance, but not absolute assurance, that the objectives can be achieved.

4.7.2. Resources

Being a small, not-for-profit organisation, the availability of resources is a huge constraint for ABC. Its constraints in terms of finances, talents, and catalyst for change are discussed further below.

4.7.2.1. Financial Resources

Financial resources are big challenges for ABC as it has limited accumulated reserves and cash in the bank. The COVID-19 pandemic has made it worse for the organisation as many of its training courses were cancelled, resulting in lower revenue. On the other hand, its main expenses, such as rental and manpower costs, remain the same.

However, an interesting lesson is drawn from this project – despite the lack of profitability, ABC has invested to upgrade its membership database in 2020 to better capture members’ information. One of the interview participants has said that data analytics is so important that the organisation must resolve the funding issues to implement it. Most of the participants have also expressed confidence that financial constraints are not the stumbling block for launching data analytics strategies in ABC.

The above demonstrates that if the leaders and staff recognise the importance of data analytics, they will collectively lead the organisations to overcome financial constraints. In contrast, if there is a lack of awareness, financial constraints are likely excuses for not implementing data analytics strategies.

Therefore, it is important to educate the leaders and staff in SMEs about the importance of data analytics. Once they understand that data analytics is paramount for their survival, they will lead their organisations to overcome other constraints to successfully launch data analytics strategies. There are opportunities for academia to play an important role to communicate and promote the benefits of data analytics to SMEs and not-for-profit organisations.

4.7.2.2. Talents and Skills

There is a lack of data analytics skills among the staff employed by ABC, as confirmed during the semi-structured interviews. Among the data analytics tools, they are familiar only with Microsoft Excel spreadsheets. However, the participants are fully aware that they need to pick up data analytics skills to stay relevant in the job market. During the second interview, one participant clarified that the staff does not have data analytics skills because they did not need to learn such skills for their existing responsibilities. However, as the needs have arisen now, the staff is confident that such skills can be learnt.

After analysing the skill levels of the staff, the research student recommends ABC adopt Microsoft Excel spreadsheets as their preliminary data analytics tool. The objective is to “start small” or take “baby steps” to allow the staff to learn new skills and gain confidence before more advanced and complex solutions are introduced. This approach also allows the organisation to save on potential financial resources to acquire sophisticated tools. After the staff has gained more confidence, more complex tools, such as Python, SQL and R can be explored.

4.7.2.3. Catalyst of Change

In this research project, the research student works as a “consultant” who collaborates with the project manager as the change agent. On many occasions, the research student reminds the staff and organisation of the milestones, target dates, and to take the next steps. This is understandable as the staff has their day-to-day responsibilities and the project is considered “over and above” their daily routine. Therefore, upon reflection, the organisation needs a catalyst to initiate and sustain change projects. For small, not-for-profit organisations like ABC, they cannot afford to employ a full-time employee to act as the catalyst, therefore, the change catalyst is likely to be someone outside the organisation, as a consultant. There exist opportunities for the communities, such as government agencies and academia, to act as consultants or change agents for small, not-for-profit organisations.

4.8. Chapter Summary

Section 4.2 provides information about the case study organisation’s background, strategic goals, and structure, which illustrate the reasons for selecting it for the case study in this research project.

Through sections 4.3 to 4.4, this chapter analyses the data collected through semi-structured interviews and archival records to identify the challenges that ABC encounters when it launches a data-driven, contextual marketing strategy. The main challenges are data and resources availabilities. The analyses address:

- Research question - What are the challenges and constraints to implementing data analytics strategies in small, not-for-profit organisations in Singapore?
- Research aim - Identify challenges and constraints to implement data analytics strategies in small, not-for-profit organisations.
- Research objective - Analyse key challenges to implementing data analytics strategies confronting the not-for-profit organisation, in Singapore, with limited resources and know-how, through interviews and review of archival records.

In section 4.5, the chapter analyses the list of training courses provided by ABC and provides suggestions on coding the courses to facilitate data analytics. The section also reviews the members' information and suggests tools to be used for mapping the training courses to members, depending on their profiles. These works address:

- Research question - How can small, not-for-profit organisations in Singapore, with limited know-how and resources, successfully implement data analytics strategies?
- Research aim - Evaluate options and provide suitable advice to implement data-driven, contextual marketing strategies for small, not-for-profit organisations.

In addition, section 4.5 also addresses the following research objectives:

- Identify the required information in the member's database that is required to devise segmentation and contextual marketing strategies.
- Recommend suitable data analytics tools to implement data-driven, contextual marketing strategies for the small, not-for-profit organisation, bearing in mind the challenges and constraints confronting the organisation.
- Formulate a change management plan to transform the “one-size fit all” marketing strategy into data-driven, contextual marketing strategies.

Through sections 4.6 and 4.7, the research student reflects upon the experiences gained through the research project to draw lessons learnt that can be added to the body of knowledge, for both practitioners and academia. The identified critical success factors and constraints can be used by other small, not-for-profit organisations to increase the chances of success when they implement data analytics strategies. Therefore, by doing so, the two sections address the following research objectives:

- Through reflection, thoroughly review the drawbacks and provide recommendations for small organisations to enhance their implementation strategies.

Chapter 5. Conclusion, Limitations, and Future Work

5.1. Preamble

This chapter starts with a recapitulation of the research questions and aims in section 5.2, before discussing the contributions to the professional practices in section 5.3, and academic knowledge in section 5.4. Research limitations are deliberated in section 5.5 before recommendations for future research are made in section 5.6. The chapter ends with a summary in section 5.7.

5.2. Recapitulate the Research Questions and Aims

Before the discussions of research contributions to the body of knowledge for professional practices and academia, it is noteworthy to recapitulate the triggers of this research project, research questions, and research aims.

This research project is triggered by the research gaps, as there are few research works on implementations of data analytics strategies for small, not-for-profit organisations in Singapore. The gaps have led to the formulation of research questions:

1) What are the challenges and constraints to implementing data analytics strategies in small, not-for-profit organisations in Singapore?
2) How can small, not-for-profit organisations in Singapore, with limited know-how and resources, successfully implement data analytics strategies?

This research project strives to answer the research questions by adopting qualitative methodology, using a small, not-for-profit organisation in Singapore as a case study. The research aims include:

1) Identify challenges and constraints to implement data analytics strategies in small, not-for-profit organisations.
2) Evaluate options and provide suitable advice to implement data-driven, contextual marketing strategies for small, not-for-profit organisations.

In response to the research questions, this research project has identified challenges, which may be similar or different when compared to those noted in the literature review. The findings are presented in chapter 4 of this research project. The implications of the findings, which are worthy contributions to the body of knowledge, are discussed below.

5.3. Research Contribution to Professional Practices

Many data analytics implementation projects have ended as failures, due to reasons such as lack of leadership support (Gartner, 2018; Ransbotham et al., 2016; McAfee and Brynolfsson, 2012), and employee resistance (Microsoft and ASME, 2018; Wills, 2014; Tamilarasu, 2012; Griffith-Cooper, 2007). Due to limited resources at their disposal, small, not-for-profit organisations can hardly afford such failures. However, there is no guidance for small, not-for-profit organisations as there is little research done for them, especially in Singapore.

This research project targets to fill the gap by proposing a framework to guide small, not-for-profit organisations to launch data analytics strategies successfully. By putting together the knowledge noted in the literature review and the practical experience gained through implementing the data analytics strategy for ABC, the research student has proposed a 5 “Os” framework.

This is the first framework to guide small, not-for-profit organisations in Singapore to implement data analytics strategies. The adoption of the framework can increase the chances of success in data analytics strategy implementations. Therefore, the 5 “Os” framework is considered as the main contribution to professional practices for this research project.

5.3.1. Proposed 5 “Os” Framework to Guide Future Data Analytics Projects

As discussed previously in this research project, many implementation projects have ended as failures and small, not-for-profit organisations can hardly afford such failures. Therefore, this research project uses prior knowledge, which is strengthened with implementation experience to propose a 5 “Os” framework.

The 5 “Os” stand for: (a) open opportunity, (b) organise, (c) obtain data, (d) observe, and (e) optimise. They are discussed in the following sections.

5.3.1.1. Open opportunity

As change management projects must start with a clear purpose, which must be articulated by the project owner (Andersen, 2012), ABC has started well by analysing its strengths, weaknesses, opportunities, and threats to identify the reasons for changes. The underlying reasons to change were articulated to the staff. These have reduced staff resistance. Therefore, small, not-for-profit organisations that are embarking on data analytics strategy must identify the reasons for changes, list the opportunities and constraints for clear communications to the staff.

5.3.1.2. Organise

After formulating a clear purpose to change, the next step is to organise a project team to drive the implementation. The composition of the project teams and the suitability of project managers are critical. The success of the projects is correlated to the attitudes of the project manager (Andersen; 2012; Muller and Turner, 2010).

Leaderships also play a critical role to determine the success or failure to implement data analytics strategies (Gartner, 2018; McAfee and Brynjolfsson, 2012; Ransbotham et al., 2016). In the case of ABC, as discussed in the previous chapter, strong leadership support is the cornerstone of success.

Therefore, the leaders of small, not-for-profit organisations that intend to launch data analytics strategies must be convinced that the strategies are important for the long-term survival of their organisations. Once the leaders are convinced, the next step is to convey the need for changes to gain support throughout the organisations and form a project team.

5.3.1.3. Obtain data

Although ABC upgraded its membership database, it will take at least a year for members to update their profiles before data analytics can be performed. This experience shows that small, not-for-profit organisations must check whether essential data are available at the start of the project, ideally during the conceptualisation stage. On the other hand, they must also be cognisant that the “perfect” data may not exist. Judgment calls are required to balance between the amount of data required and the costs to obtain incremental data.

5.3.1.4. Observe

ABC has decided to take "baby steps" by starting small, gain experience and confidence before launching data analytics strategies at a larger scale. Small, not-for-profit organisations are encouraged to "start small" and allow the organisations to adjust before going full scale (Bump, 2015; McAfee and Brynjolfsson, 2012). The organisations can choose an area with the most potential benefits within the shortest timeframe for piloting the strategies (Alibaba Cloud, 2018; DBS, 2014).

5.3.1.5. Optimise

After 'starting small' and allow the organisations to adjust, they can decide to scale up once the leadership teams and staff are ready to optimise the strategies (Bump, 2015; McAfee and Brynjolfsson, 2012)..

5.3.1.6. Checklist for the 5 "Os" framework

The above discussions of the 5 "Os" framework can be summarised in a checklist, as shown in Table 5.1 below. It is expected to facilitate smoother implementations by avoiding the pitfalls encountered by ABC. However, it is noted that the checklist is in the infant stage, hence with more research works and usages, the checklist will be enriched with more pearls of wisdom and insights.

	5 "Os"	**Checklist**
1.	Open opportunity	a) Identify reasons to change b) Set clear business case, identify: i. Opportunities ii. Constraints
2.	Organise	a) Form project team b) Gather top management support c) Communicate opportunities d) Secure buy-in e) Set the appropriate pace for change

3.	Obtain data	a) Identity data needed for data analytics b) Check data availability c) Identify gaps d) Determine analytics can be performed with available data e) Cleanse data f) Identify data analytics tools g) Build prototype
4.	Observe	a) Implement changes on small scale or do a parallel run b) Provide training c) Review outcome and adjust
5.	Optimise	a) Roll out data analytics strategies on a bigger scale b) Cutover to the new process, stop the parallel run

Table 5.1: Implementation Checklist based on the 5 "Os" Framework

Although the focus of this project is an organisation in Singapore, the lessons learnt from this project, and the 5 "Os" framework should also be useful for organisations with a similar set-up, even if they are outside Singapore. As the framework includes both the success factors and lessons learnt from the pitfalls, other small, not-for-profit organisations can benefit from the ABC's experience if they use the framework. This would lead them to a greater chance of success in their implementations. Thus, the framework is filling the gap identified earlier concerning no guidance for small, not-for-profit organisations, especially those in Singapore, to launch their data analytics strategies.

However, the 5 "Os" framework must be used with appropriate customisations, taking into consideration of the organisation culture, as well as regulations, cultures, and practices in various countries.

5.3.2. Data Management Problems are Not Confined to Big Data

From the literature review, it is generally argued that data management issues exist because of high data volume and velocity (Ransbotham et al., 2016; Segarra et al., 2016; Cheng et al., 2015).

Contrary to those findings, this research project reveals that the case study organisation faces severe data management issues although it does not have high volume nor high-velocity data. ABC faces different challenges from those encountered by the big, commercial organisations, as there is a lack of relevant data for accurate data analytics. Furthermore, where limited data is available, they are stored in fragmented manners, such as in Excel spreadsheets located in different folders.

This research project reveals that small, not-for-profit organisations must cater for lead time to prepare for data. As ABC needs at least another 12 months to collate its data before it can perform meaningful data analytics, the implementation timeline is prolonged.

5.3.3. The attitude of Leaderships Can Overcome Funding Challenges

Many SMEs owners and key decision-makers are not aware of the benefits to be derived from digital transformation and data analytics (Microsoft and ASME, 2018). The lack of awareness has led to the wrong perceptions that the data analytics implementations are costly (Microsoft and ASME, 2018; Ogbuokiri et al., 2015) and those data analytic strategies are too complex for SMEs (Microsoft and ASME, 2018; Ogbuokiri et al., 2015), and hence data analytics are designed for large orgaisations (Ogbuokiri et al., 2015).

Contrary to the general observations made in the literature reviews, participants of this research project opined that ABC could overcome the challenge due to limited funding. Firstly, they do not expect launching data analytics strategies to require huge investment. Secondly, they view data analytics strategies as an essence for the organisation to survive. They opined that it is necessary to source for the fund if needed.

The above observations illustrate that when the leader believes in the importance of data analytics strategies, they will overcome the challenges, including shortage of funds. The leadership and staff in ABC understand the importance of data analytics, as they are exposed to the latest trends through seminars that they attend regularly.

With the above knowledge, policymakers must target leaders in small, not-for-profit organisations to communicate the benefits of data analytics strategies. Once the leaders understand the urgency to embrace data analytics, they will lead their organisations to do so, like ABC.

5.3.4. Paces of Change Determine the Success Rates

Alibaba Cloud (2018) and Bump (2015) have proposed to implement data analytics strategies in stages. The management of ABC has taken the same approach to implement data analytics using contextual marketing for training courses as the pilot. By doing so, minimises the anxiety among the staff, and reduces the impact should the strategy turn up to be unsuitable for the organisation. The staff has requested to do a parallel run until they are confident that the new strategy works well. This demonstrates the anxiety if the new strategy is implemented too fast, e.g., cut over to the new strategy immediately.

This experience confirms the recommendations from Alibaba Cloud (2018) and Bump (2015); hence, small, not-for-profit organisations are advised to implement data analytics strategies in stages to curb staff anxiety and allow the learning curve effect to kick in before launching the strategies in bigger scale.

5.4. Research Contribution to Academic Knowledge

The observations from this research project are compared against those made in the literature reviews, to draw lessons learnt, which can be added to the body of knowledge for academia. The sub-sections below provide greater details.

5.4.1. Formulation of a New Framework

As discussed in Section 5.3, the proposed 5 "Os" framework is the main research contribution to professional practices. However, it can also contribute to academic knowledge.

The framework is formulated using a case study approach, which is meant to be explorative, as there is limited research in this area. The 5 "Os" framework is expected to arouse research interest for not-for-profit organisations, especially those in Singapore, and concurrently it forms the groundwork that future research can build upon. The research student is hopeful that more attention will be attracted to the area and more research would be done using not-for-profit organisations in Singapore.

5.4.2. New Observations – System Readiness

For small, not-for-profit organisations, data may not be readily available because they may not be collated in a systematic manner in a centralised system. In the case of ABC, data are either not available or are recorded in various Excel spreadsheets. This may not be raised in past research works, which are performed using big, commercial organisations. Small, not-for-profit organisations may not have the resources to invest in systems to capture the necessary data and therefore resort to using spreadsheets.

5.4.3. New Observations - Leaderships

Leaderships, talents, and funding are key challenges raised in the literature reviews. In contrast, the case study organisation has raised leadership support as a key strength. The talent shortage is raised as a gap, but ABC is confident in upskilling its staff without incurring high costs. Similarly, ABC considers funding as a challenge that should, and can, be overcome because digitalisation and data analytics are essential for survival.

The differences in observations between the case study organisation and literature reviews provide new perspectives in the quest to encourage more organisations to embrace data analytics strategies.

Based on the literature reviews, the slow adoption of data analytics strategies among the SMEs can be attributed to the lack of awareness by the owners and decision-makers (Microsoft and ASME, 2018), leading to the wrong perceptions that data analytics strategies are complex and expensive (Microsoft and ASME, 2018; Ogbuokiri et al., 2015).

The situation at ABC demonstrates that once the leaders have a clear understanding of data analytics, they are willing to take "baby steps" and use simpler tools, such as Microsoft Excel to kick start the data analytics strategies.

Taking the two contrasting situations together, there are opportunities for academia to play a key role in raising awareness at the owners and key decision-makers to help them embark on data analytics strategies. More research works can be performed to raise awareness.

5.4.4. Opportunities for Academia - Training

There is a severe shortage of staff to enable industries to digitalise (CSA, 2019), training is in hot demand. This research has reinforced that there are values for research in the areas of digitalisation and data analytics, especially in Singapore.

The Singapore ministers have reiterated that the government alone cannot train enough talents to fill the shortage of talents, and it needs the collaboration of the communities, including academia, to fill the gaps (CSA, 2020). Therefore, there are opportunities for academia to play a more proactive role in designing and delivering courses to train Singapore's talents and improve their skills. The skill levels can be catered to small, not-for-profit organisations as they may not need complex skillsets. With better skills, the talents are equipped to help their organisation in digitalisation and data analytics.

Specifically, this research project has demonstrated that leaderships play a key role in the success to implement data analytics strategies. When top management understands the importance of data analytics, they will lead the organisation to overcome other constraints. Therefore, this research project has identified gaps, which can be turned into opportunities, to design courses that are targeted at the top leaders in small, not-for-profit organisations, to communicate the urgent needs to embrace digitalisation and data analytics.

5.5. Research Limitations

While identifying the body of knowledge for professionals and academia, it is acknowledged that this research project has limitations, for example, in terms of geographical coverage, methodological choice, and organisational structure of the case study organisation. These limitations, however, do not undermine the significance of the findings in this research work.

5.5.1. Geographical constraint

This research project is using one case study organisation located in Singapore for an in-depth understanding of the challenges to implement data analytics strategies. The research participants work in Singapore, therefore, the insights and opinions are made in the context of Singapore, as opposed to being regional or global. To enrich the body of knowledge, similar research can be carried out using similar organisations in neighbouring countries. This would ascertain the similarities and differences across countries in the same region.

In addition, as there is little prior research work performed for small, not-for-profit organisations in this part of the world, the historical literature being reviewed relates mainly to commercial organisations in the United States and Europe, as opposed to being Singapore-specific.

5.5.2. Methodological constraint

As qualitative research is adopted for this research project, the findings may be subjected to researcher bias. The research student is mindful of the weaknesses of qualitative research, constant reminders were put up during the research process to stay objective and steps, such as triangulation, were adopted to reduce personal bias.

In addition, this research project has adopted a case study approach, which is frequently questioned whether the findings can be generalised (Singh, 2014; Marrelli, 2007; Tellis, 1997). However, it has been established that a case study, which is using one organisation for an in-depth understanding of the wider class, can be generalised (Lee et al., 2007; Gerring, 2004).

Notwithstanding that the findings can be generalised, further research using the quantitative method would be useful to confirm the understandings of this research project and to ascertain whether the findings can be influenced by organisational and cultural differences.

5.5.3. Data availability constraint

As the case study organisation is in the process of collating its member information, data are not available for the project to test the data analytics mapping tool. Therefore, the artifact that will be used for the contextual marketing strategy cannot be properly developed. However, it is noted that the challenges are properly explained, and satisfactory solutions are proposed. These have achieved the “problem definition” and “solution” as proposed by Dresch et al. (2014), who acknowledged that most research works performed by professionals in organisations could not complete all the stages in DSR. Therefore, this is not considered a failure.

5.5.4. Organisational constraint

As the research area of this project is focusing on small, not-for-profit organisations, the organisation selected for the case study employs only 11 staff, hence, limiting the number of participants available for interviews. Instead of random sampling, purposive sampling is adopted as recommended by Kerr et al. (2010), Marrelli (2007), and Hood (2006). This enables the findings to be generalised with 15 to 30 interviews (Marshall et al., 2013) with 2 to 3 interviews per person (Morse, 2000). However, caution must be exercised when applying the findings to other organisations, especially organisations with staff who have different profiles and exposures to data analytics.

It is important to note that the case study organisation is a not-for-profit organisation serving professionals. The employees are frequently exposed to emerging topics like data analytics. The exposures may have contributed to the employees (who are interviewed) being well aware of the need for digitalisation and the importance of data analytics. This observation is contrasting with the findings noted in the literature review, which highlighted a lack of awareness among the SMEs (Microsoft and ASME, 2018; Ogbuokiri et al., 2015). The reasons behind the contrasting observations are not clear at this moment, hence more researches are needed to ascertain them. Research works are also required to ascertain the proportion of small, not-for-profit organisations displaying characteristics, attitudes, beliefs, and culture that conform with this research project.

5.6. Recommendation for Future Research

As this research project is designed to focus on small, not-for-profit organisations in Singapore, the findings of this research project can be the springboard for future researches for small, not-for-profit organisations in the region, Asia, or even the entire globe.

Due to the limited prior literature for launching data analytics strategies for small, not-for-profit organisations, this research project has adopted a qualitative case study approach, which is useful for exploratory researches (Yin, 2003; Tellis, 1997). Future researches on the same topics but using different research methodology, such as a quantitative survey, would be useful to confirm the findings in this research project.

Given the case study organisation is uniquely positioned as its employees are exposed to emerging topics, such as data analytics, future researches can be expanded to cover other not-for-profit organisations with different staff profiles. This may uncover different challenges to launch data analytics strategies.

It is also noted that data analytics is a fast-evolving field where new technology can replace the older ones within a short period. Therefore, future researches can look into new challenges for implementing data analytics strategies as time and technology evolve.

Due to the time constraint, the effectiveness of implementing data analytics strategy in small, not-for-profit organisations cannot be measured in this research project. Future work can be longitudinal researches (Fox et al., 2017), typically aim to understand changes over time (Bryman and Bell, 2011).

5.7. Chapter Summary

This chapter starts with a recapitulation of the research questions and aims in section 5.2, before discussing the contributions to the professional practices in section 5.3, and academic knowledge in section 5.4. Using a combination of knowledge drawn from literature review and strategy implementation at the case study organisation, this research project has proposed a 5 “Os” framework to assist small, not-for-profit organisations launch their data analytics strategies. The importance of leadership and the opportunities to design courses are highlighted. The 5 “Os” framework is expected to add knowledge to professional practices. At the same time, it is hopeful that it will attract more research on data analytics to be done for small, not-for-profit organisations to add to the body of academic knowledge.

Research limitations, relating to geographical, methodological, and organisational are discussed in section 5.5 before recommendations for future researches, for example, with different geographical coverages and research methodologies, are made in section 5.6.

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Appendix 1 – Interview questions

Interview Questions:

(1) Compared to the current practice of mass email marketing, what are the advantages and disadvantages of data driven, contextual marketing?
(2) What do you know about data driven, contextual marketing?
(3) What do you foresee as the challenges for the organisation to change the practices from mass email marketing to data driven, contextual marketing? (Cultural wise? Data collection wise? Process wise? IT System wise? Infrastructure? Staff attitude aspect? Reputation?)
(4) What are the likely impacts to your job by implementing data driven, contextual marketing?
(5) What do you think the organisation should do to equip you for the new (data driven) strategy?
(6) What can the organisation do to successfully implement data driven, contextual marketing? (Cultural wise? Data collection wise? Process wise? System wise? Infrastructure? Staff attitude aspect? Reputation?)
(7) Do you think the organisation can do more with data analytics? Why?

Appendix 2 – Publication by Research Student

Sia NC (2018) The challenges for a small not-for-profit organization to embark on data analytics strategy. Amity Bus Journal 5(1):18

Sia N.C., Hosseinian-Far A., Toe T.T. (2021) Reasons Behind Poor Cybersecurity Readiness of Singapore's Small Organizations: Reveal by Case Studies. In: Jahankhani H., Jamal A., Lawson S. (eds) Cybersecurity, Privacy and Freedom Protection in the Connected World. Advanced Sciences and Technologies for Security Applications. Springer, Cham. https://doi.org/10.1007/978-3-030-68534-8_17