

Marketing intelligence system implementation in B2B service marketing environment An explorative case study

Master thesis submitted to Delft University of Technology
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

In

Management of Technology

Faculty of Technology, Policy and Management

by

Kavish Kowlesar

Student number: 4141768

To be defended in public on 30th of August 2019

Graduation committee

Chairperson	: Dr. S. W. Cunningham, Section Policy Analysis (TPM)
First Supervisor	: Dr. L. Rook, Section Economics of Technology and Innovation (TPM)

Project Details

TITLE

Marketing intelligence system implementation in B2B service marketing environment

SUBTITLE

An explorative case study

KEYWORDS

Marketing intelligence system, marketing information system, information needs
professional services, IT consulting

AUTHOR

Kavish Kowlesar
Student number 4141768

PROGRAM AND EDUCATIONAL INSTITUTION

Master program Management of Technology
Faculty of Technology, Policy and Management
Delft University of Technology
Delft, the Netherlands

GRADUATION COMMITTEE

First supervisor
Dr. Laurens Rook
Assistant Professor at section Technology, Strategy and Entrepreneurship

Chair
Dr. Scott Cunningham
Associate Professor at section Policy Analysis

NUMBER OF PAGES OF THIS REPORT

112

VERSION

Final document

Preface and acknowledgement

In front of you lies my master thesis 'Marketing intelligence system implementation in B2B service marketing environment an explorative case study' that is written as a partial requirement for the degree of Master of Science in Management of Technology. The motivation to write about this topic originates from an interest of both me and the marketing and communication department of Capgemini. Months of work and energy went into this final document. Not only did the work on this document teach me about doing research on academic degree, it also taught me several lessons spanning a wide range of topics both professional and personal. From the silly conversations with coworkers and supervisors at the sponsoring firm to stressful solitary moments moment scanning through enormous amounts of documents, the journey has lead me to much growth.

Several actors have contributed to the journey. First I would like to thank my first supervisor Dr. Laurens Rook for his guidance and feedback during the project. His helpful tips during our meetings and his friendly approach during confusing times helped me in finding direction. I enjoyed working with him. I would also like to thank my chair Dr. Scott Cunningham for his valuable feedback, his patience and for agreeing to be part of my thesis committee.

Furthermore, I would like to thank the team at Capgemini for granting me the opportunity for this research and to get an impression of the organization. Special thanks to my project committee Francien Buylickx, Kees van den Hout and Jos van Rijn who introduced me into the company and helped me during the initial stages of the projects. The weekly meetings and talks with external companies not only gave me a good view of the company, but also gave me valuable experiences that will definitely be useful in my career.

Finally I would like to thank my parents for unwavering support and love during the journey, to my brother Pravin for his inspirational messages that kept me going through rough times and my friends for the endless talks that functioned as outlet. A special thanks to my dearest friend Rachelle who, next to listening to the endless talks, also helped proofreading and acted as the valuable second coder.

Executive summary

PROBLEM

The business and marketing environments of today are rapidly changing due to several trends in society and in the market (Kotler & Keller, 2016). To maintain their position, companies must continually renew their knowledge management systems. The emergence of information technology (IT)-based intelligence systems suggests more possibilities for gathering knowledge than ever before. These possibilities can help to better meet the information needs of marketers in corporate setting.

Sparked by implementation of such technologies in the business-to-consumer (B2C) marketing environment, business-to-business (B2B) marketers of the case firm (an IT consulting company) were interested in the possibilities that implementation of state-of-the-art IT based intelligence systems would offer for meeting their information needs. The objective of this research was, therefore, to explore the possibilities of intelligence systems that could add to the marketing information system of B2B marketers. This resulted in the following research question:

How should an intelligence system look like to effectively add to the B2B marketing information system of an IT solution consulting company?

The literature suggests that differences exist between B2B and B2C marketing. These differences point to different intelligence needs in B2B, which should be met with a different marketing information system. However, literature on the specific intelligence needs of B2B marketers and their marketing information system was not available. Furthermore, the existing literature provides enough knowledge on intelligence systems, but lacked on specific knowledge on IT based marketing intelligence systems, let alone marketing intelligence systems designed specifically for B2B marketing.

Based on the available literature on overall intelligence systems, a framework was made that combined several methods and possibilities for intelligence systems. By adding challenges for implementation, this framework could help in determining how an intelligence system for specific purposes would look like. The identified gaps of the literature, combined with the challenges for implementation for intelligence system provide an overview of what information is needed about the B2B marketing environment to answer the research question.

METHODOLOGY

The information needed for answering the research question was extracted by means of an embedded case study on an IT consulting company. Several units of analysis were distinguished, based on general approaches to B2B marketing. In-depth semi structured interviews with the marketers within the case company were used to gather data. The topics were based on the information gaps in the literature, combined with knowledge from several resources about the marketing environment such as observation, available documentary and introductory interviews. The interviews were transcribed and coded using specialized software (Atlas TI). The analysis focused on finding relationships between key concepts found in the interviews.

FINDINGS

By using this methodology, three phenomena were found. First, by linking the available marketing information system with the marketing needs that were suggested by the marketers, gaps could be identified, which could be used in the development of an intelligence system tailored to the needs of the case company. Converging evidence was found between the identified units of analysis suggesting the existence of an intelligence gap for knowledge on the people working at their customers. Specifically, the B2B marketing information system does provide information on customers, however does so on (too) high (read: general) an abstraction level. The B2B marketers indicated a need for information on a lower (read: more personal and precise) abstraction level, specifically: interest, hobbies, roles, activities, how they are linked together and whether they are part of a decision making unit.

Second, the interviews also produced a list of potential data sources for an intelligence system. Scoping these sources towards the needed intelligence suggest that an intelligence system should make use of user-generated content (i.e. social media, blogs and forums), online published interviews and surveys. These sources might contain relevant information, but they are in textual unstructured format. Finally, the preferences for presenting the intelligence were extracted from the marketers. The marketers would prefer intelligence presentation to be implemented in other systems. They would like to have a search option, and they preferred easy to use display of the intelligence.

PRACTICAL IMPLICATIONS

Based on the found phenomena, choices could be made using the framework for intelligence system implementation based of the literature. The proposed intelligence system design was built from the following layers: (1) the intelligence system will use user-generated content (UGC) (i.e. social media, blogs and forums), online published interviews, and surveys as data source. (2), Data will be extracted from these sources using natural language processing methods such as named entity recognition, relationship extraction and sentiment analysis. (3) The extracted data will be stored in databases. (4) OLAP servers will be used for slicing and dicing of the data. (5) The data will be presented as intelligence by use of searchable relational graphs. This form of presentation could be implemented in dashboards of other systems such as the marketers' CRM system.

The intelligence system can add to the marketing information system by providing valuable insight on customers on a lower (read: more personal and precise) abstraction level. This form of intelligence is useful to the marketers, but is not currently provided decently by existing B2B marketing information systems.

Table of contents

Chapter 1: Introduction

1.1 Intelligence systems in Business to business marketing environment	1
1.2 Research background	2
1.3 Research Objective and Scope Definition	2
1.4 Research questions.....	3
1.5 Research Methodology	3
1.6 Structure of the report.....	4

Chapter 2: Literature review

2.1 marketing	7
2.1.1 B2B marketing	8
2.1.2 The marketing information system	9
2.1.3 Marketing intelligence and intelligence systems	11
2.2 Intelligence systems	12
2.2.1 Early intelligence systems	12
2.2.2 Current intelligence systems	14
2.2.3 Challenges for implementation	18
2.3 Finding the intelligence needs.....	20
2.4 Summary.....	22

Chapter 3: Methodology

3.1 Justification.....	25
3.2 Case study design	26
3.3 Research strategy	28
3.3.1 Preparation.....	28
3.3.2 Data collection.....	31
3.3.3 Data analysis.....	33
3.4 Validity and reliability.....	35
3.5 Summary.....	36

Chapter 4: Research findings

4.1 Units of analysis findings	38
4.1.1 Sector based marketing (SBM) managers	38

4.1.2 Portfolio based marketing (PBM) managers	41
4.1.3 Account executives/Key account manager (KAM)	44
4.2 sources.....	47
4.3 Conclusion of the findings	49

Chapter 5 Discussion and conclusion

5.1 Main findings	51
5.1.1 B2B environment.....	51
5.1.2 Choices for intelligence systems	52
5.1.3 Intelligence system	55
5.2 Reflection on the system	58
5.2.1 Reflection on the choices	58
5.2.2 Reflection on the intelligence system	59
5.3 Strengths and limitations	60
5.4 Future research	61
5.5 Research Contributions	62
5.6 MOT curriculum alignment	64
5.7 Conclusion	64

<i>Bibliography</i>	64
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Appendices

A. Topic list interview Marketing and sales	79
B. Inter-coder reliability.....	80
C. Networks of codes and diagrams	82
D. Machine learning.....	88
E. Natural language processing	93
G. GDPR.....	101
H. Sumerized literature table for intelligence system implementation	101

List of Tables and figures

Table 1 Johari window: Needs and intelligence streams	21
Table 2 Research data	30
Table 3 Data sources given in interview.....	47
Table 4 Inter-coder reliability coefficient	80
Table 5 Sumerized literature for intelligence system implementation.....	101
Figure 1 Three Cycle View framework (Hevner A. R., 2007)	4
Figure 2 Marketing information system as described by Kotler (2003)	11
Figure 3 hypermedia system, SPRINT (Ram & Carlson, 1990).....	13
Figure 4 Cluster visualization (Reinschmidt & Francoise, 2000).....	14
Figure 5 Relational graph visualization (Petermann, Junghanns, Müller, & Rahm, 2014)	17
Figure 6 Framework with possibilities for an intelligence system	19
Figure 7 Conceptual framework for data extraction	23
Figure 8 Visual summary of the case study approach.....	27
Figure 9 Interview process (Spruijt, 2016)	32
Figure 10 Concept map intelligence needs SBM	39
Figure 11 Concept map intelligence streams SBM.....	40
Figure 12 linkages intelligence needs and streams SBM	41
Figure 13 Concept map intelligence needs PBM.....	42
Figure 14 Concept map intelligence streams PBM	43
Figure 15 linkages intelligence needs and streams PBM	43
Figure 16 Concept map intelligence needs account executives	45
Figure 17 Concept map intelligence streams account executives	46
Figure 18 linkages intelligence needs and streams account executives	46
Figure 19 linkages codes data sources	48
Figure 20 Overview intelligence system for B2B marketing	57
Figure 21 Function ABM.....	82
Figure 22 Presentation preferences sector based marketers	82
Figure 23 Information streams sector based marketers.....	84
Figure 24 Information needs sector based marketer.....	83
Figure 25 Function portfolio marketeers	84
Figure 26 Presentation preferences portfolio based marketers	84
Figure 27 Information needs portfolio based marketers	85
Figure 28 Information streams portfolio based marketers.....	85
Figure 29 Function account executives.....	85
Figure 30 Presentation preferences account executives	86
Figure 31 Information streams account executives.....	88
Figure 32 Information needs account executives.....	87
Figure 33 Correlation between complexity and available training data (Russell & Norvig, 2009).....	88
Figure 34 Reinforcement learning (Kaelbling, Littman, & Moore, 1996)	91
Figure 35 Different machine learning algorithms	92
Figure 36 Broad Classification of NLP (Khurana, Koli, Khatter, & Singh, 2017)	94
Figure 37 Webclopedia architecture (Hovy, Gerber, Hermjakob, Junk, & Lin, 2000)	95
Figure 38 Matrix structure marketing case firm	98

1 Introduction

1.1 Intelligence systems in Business to business marketing environment

The current business environment is changing due to several trends. First, societal forces such as the world getting smaller due to globalization, increasing integration and the increasing importance of corporate social responsibility, have influence on the business environment (Kotler & Keller, 2016). Second, technological developments are staggering. Processing power increasing over time, cloud computing is rising, methods for data analysis and business intelligence gathering a lot of traction and new sources for gathering information have become available with the rise of the internet and current developments of Web 2.0 and the semantic web (i.e. an internet framework that allows data to be shared and reused across application) (Shannon, 2006).

Together with the changing business environment, also the marketing environment is changing. The intense competition forces companies to innovate their marketing activities towards being more aware of their environment (Arnett & Badrinarayanan, 2005). Knowledge has become the foundation for achieving and maintaining competitive advantages. Careful planning of messages can only be done with having knowledge over the marketing environment, and knowledge is the critical component in making good and effective decisions (Leonidou & Theodosiou, 2004).

Businesses must continually renew their knowledge management to maintain their position in the market (Porter & Millar, 1985). Businesses that have useful intelligence at the right time available for the right people can act more efficiently than their competitors, gain competitive advantage and keep ahead of the competition (Zeng & Duan, 2012). It is therefore needed to be up to date on the methods for gathering useful information.

Recent technological advancement resulted in more opportunities to gather information. By gathering and utilizing data from new sources and analyzing it using new methods, it has become possible to gather data at high speeds. But, as said by Naisbitt (1982): "we are drowning in information but starved for knowledge" (p. 24). With the current rise in data, this is only enforced.

Developments in the field of ICT-based intelligence systems suggest that more knowledge could be extracted from information to fill the needs of marketers. Businesses are currently looking for initiatives using intelligence systems to extract knowledge on several facets of the market environment to help marketers in their decision making (Murad, 2010). IBM for instance launched "IBM Watson Marketing insights", a tool that can provide marketing analysts with a dynamic view of customer behaviour and the power of predictive insight. Several other intelligent recommender systems are currently being used as well, such as salesforce's commerce cloud that extracts preferences to provide customers with personalized content (Salesforce), and netflix's recommender system that ranks videos on what a member is most likely to like on two dimensions: genre (rows) and movies (columns) (Ricci, Rokach, & Shapira, 2015).

The use of intelligence tools is however more commonly used in the business to consumer (B2C) environment, while the use of such tools in the Business to business (B2B) environment is lagging behind. Traditional B2C intelligence systems are not useful in the B2B environment due the difference in marketing activities. As B2C hold more to the traditional marketing activities, quantitative methodologies are widespread while in B2B marketing these techniques are not being utilized as much (Nairn, Ede, & Naude, 2001). As an example, B2C aims to reach as many customers as possible and widen the customer base. In B2B there are high costs to acquiring new organizational customers, therefore it is more common to conduct further business with current customers (Noori & Hossein Salimi, 2005).

Filling this gap should contribute effectively help the B2B environment, especially since expenditure in B2B marketing is larger than B2C, and therefore a more substantive effect could be made with the adaption of new techniques (Berthon, Ewing, Pitt, & Naude, 2003).

This research will focus on the possibilities of intelligence systems for marketers working in the B2B sector. The importance of this research stems from the growing interests of marketers in attaining knowledge combined with the availability of several information technology (IT) based advancement in for instance: data storage, data analytics and data extraction, suggesting that more marketing needs can be fulfilled by usage of web based sources and extraction of useful knowledge out of unstructured sources towards improving relationships.

1.2 Research background

The researcher was approached by a large IT consultant in the Netherlands (Capgemini) to investigate the possibilities of intelligence systems for their B2B marketing environment. As a market leader in the field of IT solution consulting, the firm's marketing department is responsible for conveying information on the company and the available services to their corporate customers.

The rise in popularity of intelligence systems sparked an interest in the marketers to check the possibilities. The marketers were aware of intelligence system implementations in the B2C environment and were extremely curious to the possibilities for such systems in their own environment. The marketer's work was knowledge-intensive, which made them highly aware of the added value that information can bring in their day to day marketing activities. Aware that companies have to keep innovating to maintain their market position (Slotegraaf, 2012; Drucker, 1998), and given the declining market share of the firm (Capgemini, 2017), the eagerness for finding out new knowledge streams was enormous.

1.3 Research Objective and Scope Definition

This research will be carried out for the Delft university of Technology from October 2018 to August 2019 and was written in collaboration with the IT consultancy firm Capgemini the Netherlands. The present research was set up as a preparatory study for the design of a new B2B intelligence system with the aim to improve marketing information system to better meet the information needs of marketers. The objective of this thesis is to give direction to how a system would look like that can improve the marketing information system.

The objective of this research is to explore the possibilities of intelligence systems that could add to the marketing information system of B2B marketers to give direction on how such a system would look like.

This will be achieved by analyzing the information needs of the marketers and the current information streams the marketing information system provides to identify whether and how an intelligence system could add to meet the information needs given the requirements for intelligence system implementation.

It is important to stress that three research limitations come forth from this description. First, this research will only make an inventory of the information needs using intelligence systems, and, in doing so, would not take into account other possible methods to fill intelligence needs (such as human capital knowledge exchange systems (O'Leary, 1998) or observation based knowledge systems (Kotler & Keller, 2016)). Second, this research will only look at the information needs as given by the marketers, and will not go further to investigate the usefulness of the intelligence, for instance to the return on investment of the marketing efforts. Finally, the directional objective restricts this research to scoping down options towards what an additional system would look like. The researcher can thereby consult the organization. The organization is free to use the consult towards a functional design or proof of concept.

1.4 Research questions

The purpose of the research is achieved by answering the research question posed for this purpose. The main question of this research is therefore:

How should an intelligence system look like to effectively add to the B2B marketing information system of an IT solution consulting company?

The main question is supposing a number of concepts. These are: the information needs of B2B marketers, the B2B marketing information system and intelligence systems. Several sub questions are needed that break down the process in a sequential manner.

The first sub question brings attention to the knowledge that has already been researched. It looks at the concepts and helps to identify the gaps in knowledge to answer the main question,

Sub question 1: What factors from the academic literature on intelligence systems and marketing information systems are relevant for identifying the information needs of B2B marketers and possibilities for intelligence systems?

Complementary to this sub-question, an understanding of the practical situation is needed. This involves the collection of descriptive data on intelligence needs, information system streams, and aspects of the challenges for implementation.

Sub question 2: What are the overall intelligence needs and preferences of B2B marketers that can be met by an intelligence system?

Answering these sub questions will provide the information to answer the main research question.

1.5 Research Methodology

The research framework used to address the research objective and answer the research questions is inspired by Hevner's (2007) three cycle view as shown in figure 1. Hevner describes a framework with 3 iterating cycles that represent relevance, rigor and design. The goal of the cycles is to unite 3 building blocks of research being the environment which is the area for which the research is applied, the knowledge base which is a display of the scientific knowledge that is available for this research and the

design science research which is the process of development and evaluation. Hevner's framework will not be implemented literally, but will be used as inspiration.

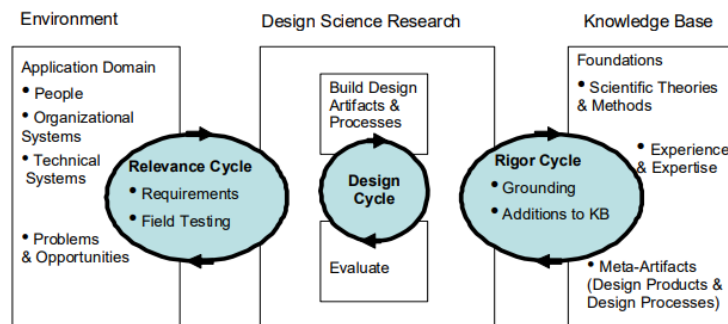


Figure 1 Three Cycle View framework (Hevner A. R., 2007)

The research will begin with a literature review on marketing, marketing information systems and intelligence systems. Such investigation lays a foundation of the knowledge base by assessing the already existing scientific theories on the subject. The outcome of this section will give an overview of the possibilities of intelligence systems together with a theoretical framework for extracting the needs of B2B marketers. This will be used in later stages of the research process and represents the starting point of the second research section, which consists of a qualitative embedded case study.

The qualitative case study approach has been chosen since it provides the possibility for an inductive, explorative and in-depth view of the marketing environment under study. The case study methodology is mentioned to be specifically useful for research questions regarding exploratory research (Yin, 2014). Case studies involve in-depth contextual analysis of matters in different settings within the scope, and are especially useful in understanding certain phenomena and gathering further theories (Sekaran & Bougie, 2010). Furthermore, it is flexible enough for studying new technologies (Yin, 2014). The approach can capture multiple phenomena of the study environment, such as a clear view of the systems in place, the needed information of the marketers and the preferences. These phenomena could be extracted from several employees within the B2B environment.

The possibilities of intelligence systems will be combined with the extracted phenomena of the environment to answer the final research question and provide a recommendation towards the implementation of an intelligence system in the B2B marketing environment.

1.6 Structure of the report

This research is structured to reflect a typical structure for scientific research. It follows a chronological sequence of events in which each chapter addresses a specific segment of the research.

Chapter 2 will cover the literature to answer the first sub questions. Literature on B2B marketing and marketing information systems will be discussed followed by literature on intelligence systems, challenges for implementation of intelligence systems and methods for extracting the information needs.

Chapter 3 proceeds by giving the methodology that suits the objectives of the research from both practical and theoretical perspective. The objective in this chapter is to determine how the needed information from the B2B environment will be extracted.

Chapter 4 will try to answer the second sub question by presenting the results. It will discuss the extracted data from of a series of interviews among stakeholders. This includes an analysis on the intelligence needs that are not filled in by current marketing information system and phenomena to determine how the B2B marketing environment can fill the challenges for implementing an intelligence system.

Chapter 5 will discuss the scientific and practical implications of the main findings. It will use the main findings to identify what an intelligence system would look like that could help fill an information need that is not filled in by the current B2B information system. It will continue to give a reflection on both the proposed intelligence system and this research.

2 Literature review

For this research to have significant grounding, the topics of marketing and marketing intelligence systems (MIS) are explored with attention toward intelligence systems and related key notions. The goal of this section is to answer the second sub question:

What factors from the academic literature on intelligence systems and marketing information systems are relevant for identifying the information needs of B2B marketers and possibilities for intelligence systems?

The chapter is divided in several main sections. Section 2.1 introduces the concepts of marketing. Special attention is given to the difference between B2B and B2C, and to what a marketing information system usually looks like. Section 2.2 goes into detail on intelligence systems. The concept is divided in two forms of intelligence systems: early intelligence systems, and current intelligence systems. Each of these is described according to a five layer framework, and the challenges for implementation are extracted. Section 2.3 gives an analysis on extracting intelligence gaps. The chapter will finish with a summary.

2.1 Marketing

In this subchapter marketing will be discussed. This subchapter will start with defining marketing and explaining the information needs of marketing. It goes on to explain the differences between business to business (B2B) and business to consumer (B2C) marketing. It will continue with describing marketing information system.

The American Marketing Association (AMA) defines marketing management as follows:

"the art and science of choosing target markets and getting, keeping, and growing customers through creating, delivering, and communicating superior customer value."

Marketing is also defined as "identifying and meeting human and social needs". An even shorter definition is given as "meeting needs portably". Selling is not defined as the most important part of marketing, as the aim is to know and understand the customer so well that the product or service sells by themselves (Kotler & Keller, 2016). To be able to sell, not only the customer, but the whole environment has to be identified and known. In addition, the famous Porter (2004) defines several forces that can shed light on what kind of information is needed.

These five forces are:

- Threat of new entry
New entries in the market add to the competition, which in term will reduce the profitability in the market.
- Buyer power
The customer has power over the firm. A transaction takes place between the firm and the customer and the relationship between those can adjust the relative power. Buyers can affect the industry's profits by, for example, demanding higher quality/service or by forcing the price down.
- Supplier power
There is a relationship between a company and its suppliers. Suppliers are able to influence the profitability in an industry by, for example, raising prices or reduce the quality of its product. Size of the company, uniqueness of the product, dependency of customers and more have effects on this.
- Threat of substitution
In most markets, multiple alternatives or substitutes are available. These are products which solve the same 'problem' as the product of Rapid Walls.
- Competitive rivalry
The amount of rivalry between the companies in the market. All the forces mentioned above have an effect on this. Other factors that influence competitive rivalry are, for example, degree of innovation, internal efficiency and sustainability.

Porters five forces model gives a clear view on information topics marketers might be interested in. There might however be differences in topic focus between marketing management aimed towards a business environment and marketing tailored towards a consumer environment.

2.1.1 B2B marketing

As the name describes, B2B marketing is accountable for the marketing of products and services toward the organizational markets, instead of to consumers. In their book, Kotler & Keller (2016) describe organizational buying, in which organizations establish the need for purchased products and services and evaluate among alternative brands and suppliers. Saeed (2011) describes it as facilitating, supplying and meeting sale and resell of products and services, and the requirements of B2B, governmental and institutional markets rather than to private retail consumers.

Although B2B has existed for thousands of years, studies toward B2B did not exist in significant number until the last couple of decades. Hadjikhani & LaPlaca (2013) mentioned in their paper that the understanding and principles of B2B used to be built on personal thoughts and interferences instead of on scientific evidence. In that same paper, they concluded that B2B is going through a stage of accelerated theory deployment. We are thus in the early stages of B2B theory deployment (Saeed, 2011).

The proceedings and technological innovation are generating new possibilities for B2B. This sparked an interest for more research towards the B2B environment. As examples, Avlonitis & Karayanni (2000) describe how the internet had a positive effect on sales management activities, market-oriented product management activities and sales performance in B2B, whereas Michaelidou, Siamagka, & Christodoulides (2011) researched the effect of social network sites on B2B branding. This trend is also visible in expenditure. Marketing managers see the potential of technology-driven marketing in B2B: An article published on eMarketer (2013) for instance states that already in 2013 the digital investment of B2B was said to have increased by almost 70%.

Business marketing versus consumer marketing

The different market structure of B2B marketing thus suggests different needs than those of B2C marketing. The main difference between both marketing orientations comes forth from mass. B2C is recognizable by their dependence on the mass market with the need to handle millions of customers efficiently, while each customer is small. Without having the capacity of handling each customer individually, B2C marketing mostly approaches the whole set of customers as a grey mass. Technology -- being able to go through large data sets -- suggests a shift from seeing customers as a grey mass towards being able to approach every person as an individual (see also Zanker, Rook, & Jannach (2019)). In B2B retention and development play a higher role. This is derived from the notion of Key Account Management (KAM) becoming more important. This approach of B2B marketing divides each customer as an account in which secure individual treatment is an element (Gummesson, 2004). General information on the customer (e.g. processes of the customers, relevant stakeholders, trends and support) is therefore more important in B2B (Wouters, 2004).

A well-established difference between B2B and B2C thus is the buyer-seller relationship. Customer relationship management (CRM) is a name given to the process of carefully managing detailed information about individual customers to maximize loyalty. It enables companies to provide excellent real-time customer service through individual account information (Kotler & Keller, 2012). Due to the differences in B2C and B2B there is a difference in what companies are looking for to manage their relationships. The difference in intelligence of interest can be explained by the difference in goals between B2C and B2B. It is more common for B2C companies to focus on attracting new consumers (Al-Weshah, 2017). CRM in B2C should provide opportunities to use information know clients better and offer more value by customized sales. Quality of the customer-firm relationship seems to be highly

dependent on the personality traits of the customer. This suggests B2C relationships to be better managed, if the personality traits of the consumers are recorded. Intelligence of these traits over the mass of customers is important. B2B, on the other hand, is highly dependent on retaining customers instead of attracting new customers. Therefore, other elements of customer intelligence might be needed to enhance relationships: customer loyalty, relationship quality, perceived service quality, trust, commitment and satisfaction. Relationship marketing, defined as deliberative actions of personnel to develop maintain and sustain strong relationships with customers, is said to be more prominently managed by B2B marketers (Rauyruen, Miller, & Barrett, 2010).

The difference between B2B and B2C, however, is reducing. Caused by a shift from a consumer society towards a networked society, a shift is currently occurring in the way in which relationships are managed in B2C. Al-Wesha (2017) for instance suggests some B2C service providers to have an increasing stake in retaining customers, whereas a study conducted by Swani, Brown, & Milne (2014) suggests B2C companies to be more embrative towards using for instance social platforms with the goal of maintaining customers. This shift is going slow; B2B still has more focus on customer retention (Cortez & Johnston, 2017). Relating this back to the 5 forces model as described by Porter (2004), B2B marketing is relatively more leaning toward handling the buyer power force.

Next to the buyer seller relationship, adoption of information technology also differs between B2C and B2B. Technology adoption is more constant and higher in B2C. Two reasons are suggested for more adoption in B2C: First, B2C has more volatile activities, with an often non-contractual nature of the relationships. A more volatile marketplace generates a greater need for detailed and accurate information on the customer. Information technology that enhances the grip on the customer is therefore needed more urgently (Sarkees, 2011). Second, in B2C relative to B2B there is more distance between the firm and its customer. Because of B2C searches to engage wider audiences, the use of quantitative methodologies in B2C marketing has been widespread for decades. B2B marketing has not embraced these methodologies to the same extent. Technological advances focus more on quantitative methods (Lilien, 2016). As a result, the adoption of intelligence technology is more widespread in B2C. Tiwari & Misra (2018) for instance describe the adoption of social CRM in B2C as the integration of social media data intelligence in the sales cycle of an organization by means of social CRM to leverage firms CRM capabilities.

The adoption of information technology in B2B is less widespread. As found by Sarkees (2011), B2B firms show a mediating effect between technological opportunism-performance relationship, while B2C firms don't show this mediating effect. First, the buying and switching behavior of B2B is partially dependent on the perception and pace of technology. Second, the market for B2B is far more heterogeneous than the B2C market -- not only in terms of customers, but also in terms of performance needs (Lilien, 2016). B2B has longer sales cycles and more complex selling approaches, while having more stakeholders invested in the decision. The heterogeneous and complex nature of B2B makes for a harder environment to implement information technology. Although the adoption of technology is not widespread in B2B, it does not suggest it is impossible. As indicated by Lilien (2016), this lack of adoption might be due to a lack of scientific research in this field, instead of a lack of possibilities.

2.1.2 The marketing information system

Marketers are responsible for identifying the changes happening to the market. The methods marketers use are disciplined methods for collecting information and time spent interacting with customers,

observing the competitors and other outside groups. The information gathered is used as a basis to perform decisions. Although some literature describes decisions made on gut feeling and intuition (Jolson, 1988; Sabnis, Chatterjee, Grewal, & Lilien, 2013), a more informed approach is suggested to be more effective (Blattberg, Kim, & Neslin, 2008). In general, marketing information systems (MKIS) provide and support the making of informed decisions.

MKIS consist of people, equipment and procedures to gather, sort, analyze, evaluate and distribute timely and accurate information to the marketers. The aspects on which such a system relies are internal company records, decision support analysis, market intelligence and marketing research (Kotler & Keller, 2016). Within these aspects, decision support systems and marketing intelligence systems are both defined as systems that provide ongoing intelligence and are therefore often used synonymously (here called marketing intelligence systems) (Noori & Hossein Salimi, 2005).

Marketing intelligence describes the set of systems and procedures that marketers use to obtain everyday information about their market environment. Sources for intelligence are newspapers, conversation with customers and intelligence systems. Internal records use information coming from internal sources like sales records, stock prices, cost and financial information. They are used to spot important opportunities. Marketing research is described as the search of information that links the marketers with their market environment in order to find opportunities, refine and evaluate action and improve understanding. Multiple resources are used such as observation, surveys and desktop research (Kotler & Keller, 2016).

Marketing intelligence and marketing research are commonly used together -- as they both provide information over the market environment. There are, however, clear differences between the two: First, marketing research is more focused toward getting insight on a the narrower view of the marketing discipline, while marketing intelligence can be described as the ability to fully understand, analyze and assess the internal and external environment associated with customers, competitors, markets, industry, and use the acquired knowledge for long and short term strategic planning Second, marketing research is concerned with solving a specific problem. The narrow scope and targeted information makes it perfect for providing specific information. Marketing intelligence, on the other hand, is concerned with preventing problems (Huster, 2005). Finally, marketing research tends to be more fragmented and on demand, while marketing intelligence systems provide a constant flow of information. Marketing research is also said to focus on past information, while intelligence systems also focus on the future (i.e., forecasting; Shajahan & Priyadharshini, 2004).

An overview of an MKIS as can be seen in figure 2.

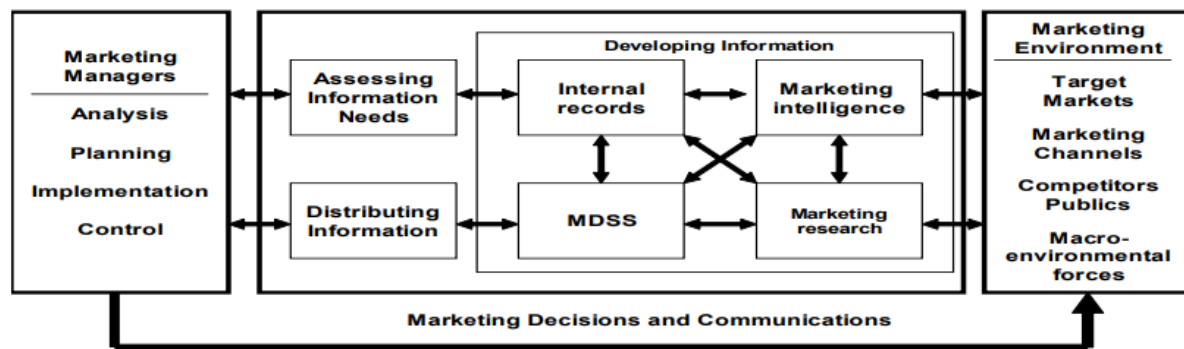


Figure 2 Marketing information system as described by Kotler (2003)

Shortcomings of MKIS

According to a study of McLeod Jr & Rogers (1985), just part of the total MKIS is utilized for decision making of marketers. Large volumes of information are served by of information streams do not specifically serve the needs of the marketers and can overwhelm and confuse the users. A good understanding of the additional intelligence needs is therefore accompanied by having a deeper understanding of the MKIS and marketing issues (Amaravadi, Samaddar, & Dutta, 1995). Elm, et al. (2005) give this as identifying the gap in support function coverage. In doing so, the support function coverage of existing tools can be analyzed.

A question is raised as to what intelligence is already being delivered by other intelligence systems in place, from marketing research or from different marketing decision support systems (Shajahan & Priyadharshini, 2004).

2.1.3 Marketing intelligence and intelligence systems

Part of the marketing information system (MKIS) is described as marketing intelligence. Marketing intelligence is known as sets of sources and procedures managers use to gather information about the marketing environment. While the main distinctive feature of marketing intelligence within the MKIS is the supply of so-called 'happening data', there are several other distinctive features of marketing intelligence over the other aspects of other information system. Firstly, information systems are described as mostly mandatory or necessary for carrying out a process, while intelligence systems are primarily optional. Users of intelligence systems are usually more educated workers. Information systems are usually better defined and based on the defining modeling process, while intelligence systems are based on the needs of decision-makers and the efficiency of the operations. Input for intelligence systems can come from internal as well as external sources (Grublješić, 2015).

The forms of information included in marketing intelligence range widely. Eerden & Rodenberg (2007) describe several aspects of marketing intelligence that give a grasp on how wide marketing intelligence reaches. Customer intelligence is focused towards getting insight in customer satisfaction, how the customer moves, attitudes of customers and customer equity. Technological Intelligence describes technological development that influences the organization. Competitor intelligence includes research and analysis of the competition, the strategies of the customer, portfolio management and future product releases. Product intelligence gives insights in the product, and pricing. Legislation intelligence

informs about rules and legislation. Finally, supplier intelligence gives insight in product development and relations with suppliers.

A system that provides marketing intelligence can thus be described as a marketing intelligence system (MIS) (Kotler & Keller, 2016). Due to a lack of current literature specifically on marketing intelligence systems (Calof & Wright, 2008), the overarching concept of intelligence system will be discussed next. Intelligence systems come in a wide variety of forms, and with a wide variety and several terms used to describe such a system. It is for instance also referred to as marketing management support system (MMSS) (Wierenga & Brugg, 1995) environmental scanning (Saxby, 2002), business intelligence (BI) (Negash, 2008), competitive intelligence system (CIS) (Nasri, 2012) and Decision Support Systems (DSS) (Power D. J., 2007; Arnott, Lizama, & Song, 2017). Also, the formulation for MKIS is sometimes also defined to be a system to provide marketers with happening data. For this study, all these systems will be referred to as intelligence systems (Leonidou L. C., 2004). The next subsection will discuss the several forms of intelligence systems.

2.2 Intelligence systems

Intelligence systems in this research encompass a wide range of solutions for gathering, consolidating, analyzing and providing access to intelligence. This is done to help practitioners make better informed decisions (Gangadharan & Swami, 2004). I will discuss several forms of early intelligence systems (analog and early mainframe based) as well as current intelligence systems (intelligence 1.0 and intelligence 2.0):

The general framework for intelligence systems consists of 5 layers. Ong, Siew, & & Wong (2011) describes four layers as: sources, data extraction, data storage and data data usage (read: analysis). Chaudhuri, Dayal, & Narasayya (2011) add a front-end layer for intelligence presentation. Each layer of the intelligence system framework is discussed for each form of intelligence system (below). Moreover, each layer presents challenges for implementation of an intelligence system. The subsection will end with giving an overview of the current intelligence system framework, and summarize all the challenges for implementation of an intelligence system.

2.2.1 Early intelligence systems

Several forms of early intelligence systems exist. Festervand, Grove, & Reidenbach (1988) describe a mostly analog intelligence system in which no technology is used. These intelligence systems were focused on knowledge management from several sources. Intelligence systems using technology come in several forms. Power (2007) describes simple mainframe systems using single source input. In this research, these simple systems all are classified as early intelligence systems. Each of the intelligence system layers will be discussed for these early intelligence systems.

Sources

Early intelligence systems relied on information from several sources. A distinction can be made between early knowledge management system sources and mainframe based system sources. Early knowledge management intelligence systems gathered knowledge from several sources, such as human capital like the sales force (Festervand, Grove, & Reidenbach, 1988), ongoing projects both internal and from competitor project summaries (Prescott, 1995), and physical observation of for instance the customers and competitors (Kotler & Keller, Marketing management, 2012).

With early mainframe-based intelligence systems, it also became possible to gather intelligence from IT-based sources. Transactional processes of systems were a useful data source (Yeoh & Koronios, 2010). An example was accounting transactions (Davis & Olson, 1985).

A challenge for implementation was the availability of knowledge of the human capital and sources. Training of the human capital could help in extracting more intelligence (Festervand, Grove, & Reidenbach, 1988; Wright & Calof, 2006).

Data extraction

From these sources, the right knowledge had to be extracted. Knowledge was extracted using several methods. Observation and reporting were methods for gathering useful knowledge. Observation of the environment for instance helped in extracting knowledge on the competitive market (Kotler & Keller, 2012).

Data for mainframe-based intelligence systems was extracted with the help of online transactional processing (OLTP) technology. This technology is able to capture useful business transactions (usually recorded against time) (Baars & Kemper, 2008).

Data storage

After the information was extracted, it had to be stored in a central place. In the case of knowledge management systems, two forms of storage took place. Information could be stored within the employees who collected the knowledge, and collected knowledge was stored with the managers. Festervand, Grove, & Reidenbach (1988) describe managers to be the central processing units (i.e., they collected all the knowledge of employees) . The manager's capabilities were therefore key to implementation of such a system. Extracted data from systems was commonly stored in simple in-house databases or spreadsheets (Cottrill, 1998).

Data usage

In knowledge management systems, the manager was the one who used the collected information. Evaluation was done by management and converted into marketing strategies. The use of information was based on the management's perceived importance and usefulness of the information. Again, the usage of the knowledge was thus highly dependent on the manager's capabilities and vision (Festervand, Grove, & Reidenbach, 1988). Early mainframe-based intelligence systems had limited (if any) form of data analysis, and were more descriptive (Prescott, 1995).

Intelligence presentation

Visualization of knowledge management systems came in the form of so-called 'thought structuring systems'. An example is the sprint system that could help represent mental models as networks. An example can be seen in figure 3 (Ram & Carlson, 1990). The data of early intelligence systems was presented in visual summaries. This helped understanding the information better – as it was hard to detect features from scanning rows and columns. Viewing the data graphically helped seeing trends. Examples are histograms and cluster visualization, as can be seen in figure 4 (Reinschmidt & Francoise, 2000)

Challenges for implementation

Early intelligence systems thus described some challenges for implementation. In the case of knowledge management systems, the main challenges were the availability of knowledge, and the capacity of the manager (Festervand, Grove, & Reidenbach, 1988). In the case of early IT based intelligence systems, the availability of (relevant) data and the need for intelligence from that data seemed to be the determining factor (Prescott, 1995).

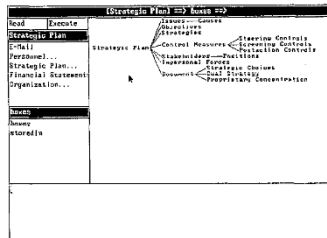


Figure 3 hypermedia system, SPRINT (Ram & Carlson, 1990).

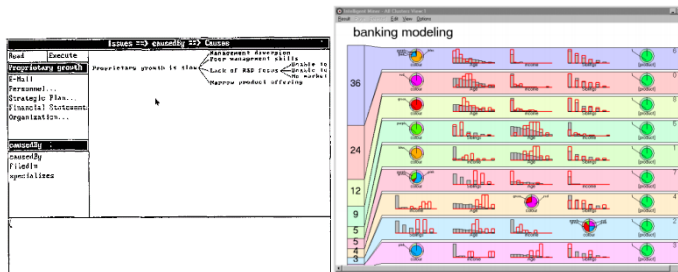


Figure 4 Cluster visualization (Reinschmidt & Francoise, 2000)

2.2.2 Current intelligence systems

More complex intelligence systems also exist. Chen, Chiang, & Storey (2012) distinguish intelligence 1.0 and intelligence 2.0. Intelligence 1.0 is described as intelligence systems that use structured sources, where intelligence 2.0 (also) uses unstructured sources. These two forms of intelligence systems are described as current intelligence systems. For each layer, the current intelligence system will be discussed with its challenges for implementation.

Sources

Sources for intelligence systems can be distinguished between sources for intelligence 1.0 and sources for intelligence 2.0. Intelligence 1.0 makes use of structured sources to extract data from (Chen, Chiang, & Storey, 2012). Several forms of structured sources are available. Tang, et al. (2017) for instance describes a system that uses sensor data to extract features and identify anomalies and hazardous events. Lei & Moon (2015) describe the use of structured market numbers. Ali, Nassif, & Capretz (2013) describe business transactions and systems transactions as structured sources. Watson and Wixom (2007) go on to describe that businesses already have systems in place that could function as a source for intelligence systems. Systems like the customer relationship management (CRM) system, enterprise resource planning (ERP) system, and the internal human resources (HR) system can be used as a valuable source. External structured sources can also be useful. Sale, Patil, & Thube, (2018) describe the use of research records of the external environment as a source for gathering data.

Developments in the field of intelligence 2.0 make it possible to -- next to structured sources -- also use unstructured sources (Chen, Chiang, & Storey, 2012). Web 2.0 provides a wide variety of unstructured user generated content (UGC) (Francia, Gallinucci, Golfarelli, & Rizzi, 2016; Schneckenberg, 2009). Meire, Ballings, & Van den Poel (2017) describe the use of social media content as an intelligence source. Likewise, Abdelmoety & Gounaris (2015) describe the use of blogs and forums as (a less biased) sources for gathering intelligence. Peer-reviewed sources as intelligence source currently also become popular. Negash (2008) for instance, describes the use of reports and researches as sources.

Sources are a determining factor for the implementation of an intelligence system. Several challenges arise, when an intelligence system is to be implemented. The availability of sources is one of these challenges (Nemec, 2012). UCG and other online sources are not always openly available. The availability should thus be checked (Bean, 2011). Finally, the sources should contain relevant information. Intelligence systems overall are focused toward fulfilling a specific intelligence need. Not all sources contain knowledge to cater to this intelligence need. It should thus contain the right information (Cortez & Johnston, 2017).

Data extraction

Data extraction refers to the transformation of sources to storable and usable data. Data that comes in a structured format can be transformed using extract transform load (ETL) tools. In doing so, data from several structured sources can be used together (Chen, Chiang, & Storey, 2012). ETL tools can differ extensively in flexibility of transformation (whether it can transform from a lot of several sources without loss of relevant information), quality (whether it produces data that is consistent and clean) and acquisition (when is data extracted, timely or trigger based).

Transactional data from business and system transactions should first be collected. OLTP tools can help in collecting this information and transforming this in usable structured data (Baars & Kemper, 2008).

Extracting structured knowledge from unstructured sources can be done by several meta-data extraction methods. In the case of textual sources, natural language processing and text mining can help in extracting data from unstructured sources. Bai (2011) for example suggest the use of sentiment analysis to extract opinions from textual sources. Xu, Liao, Li, & Song (2011), in their model, extract relationships from unstructured texts. More methods for extraction of are given in the overview of NLP in appendix E.

Implementation of the right extraction technique to derive impact is dependent on careful analysis of the application of the intelligence system together with the practitioners (Chen, Chiang, & Storey, 2012). In the case of unstructured sources, the method describes what knowledge specifically is extracted. This is highly dependent on the intelligence needs of the practitioners (Sun & Wang, 2015).

Data storage

Several methods exist for storing the extracted data. Frequently mentioned methods for storing are operational or transactional databases, data warehouses and data lakes (Botelho, 2018). Operational and transactional databases are usually smaller. The reason is that this type of storage usually only stores current data entries, and overwrites old entries. Historical data is therefore not recorded. Operational and transactional data bases sometimes only store data from a single source, although this is not always the case (Botelho, 2018; Chaudhuri, Dayal, & Narasayya, 2011).

Data warehouses are more massive, due to the inclusion of historical entries and more sources. Relational database management systems for data warehouses can be useful in storing multivariate data (Chaudhuri, Dayal, & Narasayya, 2011). Data warehouses can be used to combine multiple operational databases or log databases. Due to data warehouses being larger, it can sometimes be slower when information is needed. One method of coping with this is online analytical processing (OLAP) cubes. In that case, all possible outputs are pre-calculated (in downtime like weekends) and stored in externally. When information is needed, the OLAP cube will provide (Bălăceanu, 2007).

The final method for data storage is a data lake. Data lakes contain data in their raw form. Structured and unstructured data is stored together, commonly without preprocessing. By storing it in this form, all information is maintained. Due to this form, data lakes are a bad fit for average analytics, although this form is perfect for specific searches and as a playground for data scientists and experts (Botelho, 2018).

A single data repository might sometimes be used by multiple users who want different information out of the data warehouse. This can be solved by adding data marts. By using a single source of intelligence for multiple goals, all intelligence is consistent with each other. A high amount of requests from a repository can cost a lot of computational power. Data marts can solve this. A subset of the data warehouse is hereby extracted to be used for specific request. These subsets are usually targeted toward a specific intelligence need from a profession. (Watson & Wixom, 2007).

For data storage also some challenges arise for implementation. These challenges are mainly focused to knowing what intelligence is needed. For instance, issues relate to whether the intelligence should include historical data entries or only current entries, to whether case specific intelligence is needed, whether there is need for analyzing multiple entries, and how they relate, or whether only one form of intelligence is needed from this data base or multiple different intelligence requests. These questions all concern the intelligence need of the practitioner (Botelho, 2018).

Data usage

After storage the data must be converted to intelligence. Several methods for using the data exist. Elements can for instance be compared with each other or with other time points. The data also can be filtered to find specific segments or relationships between elements.

Chaudhuri, Dayal, & Narasayya (2011) describe several ways of using the data -- like OLAP servers and search engines. OLAP servers are data using engines designed to support multidimensional data structures and can help to expose a multidimensional view of the data. It makes it possible to filter, aggregate through the data, slice and dice the data, and pivot variables. Search engines can help to find relevant data connections between data points. These two methods for using the data are descriptive in nature.

Currently, analysis of data sets in the form of data mining can bring more opportunities. Trends and patterns can be found by using several forms of analysis. Machine learning algorithms can classify and cluster data using generic algorithms to predict future trends using time as a variable (Larson & Chang, 2016; Sun & Wang, 2015). Machine learning algorithms also make it possible to analyze multidimensional data and see patterns using more variables (Lei & Moon, 2015). Neural networks can help in finding and exploiting patterns in the data. A more elaborate overview of the machine learning possibilities is given in appendix D.

A recently emerging branch of data mining is text mining. When dealing with a lot of textual data, statistical analysis can be done over large texts or textual databases to find trends, and gather intelligence like concepts, grouping sections and finding relationships between texts (Moro, Cortez, & Rita, 2015).

The method for using data is dependent on the needed intelligence and the data source. When the source is mostly textual, text mining approaches might be considered. Next, some aspects of the needed intelligence need to be known. Do the practitioners need to have analysis done by algorithms? Do they

want a descriptive overview of the data? Do they want specific information on specific elements or topics? Again, the intelligence need is the determining factor.

Intelligence presentation

After the data is used, the intelligence needs to be conveyed to the practitioners in the form of intelligence presentations. Several forms exist for presenting the intelligence: Bălăceanu (2007) describes fixed scheduled reporting, which refers to reports delivered on fixed moments. Chaudhuri, Dayal, & Narasayya (2011) describe on-demand report. In the form of ad hoc query reports, practitioners can request reports when needed.

Data visualization can help to see trends and relationships. Visualization can for instance be done with the help of scorecards or dashboards, which can be accessed by the practitioners. Charts, colored metrics and tables can be used to give an overview of the dataset. This could be combined with the ability to view more detailed information (Ong, Siew, & Wong, 2011).

More recently, relational graphs have been used for intelligence system. Relational graphs give practitioners a quick overview of how elements are connected with each other and what the element environment looks like. An example of graph theory visualization is given in figure 5 (Petermann, Junghanns, Müller, & Rahm, 2014).

Lawton (Lawton, 2006) describes a distinction between standalone presentation and presentation integrated in another dashboard. Practitioners might already have several systems available. Adding the intelligence presentation to another system could enhance its usage.

For implementation, it should be known how the practitioners want the intelligence to be presented. Users will only rely on intelligence that they understand. The intelligence should thus be represented in a clear way, and users should be trained in the analysis and sources of the intelligence (Watson & Wixom, 2007) If the intelligence is not clearly understood, it might be deemed useful and might thus not be used (Yeoh & Koronios, 2010). Knowing how practitioners would like to have intelligence presented would help to make it easily understandable.

A complete overview of the possibilities in for a current business intelligence framework is given in figure 6.

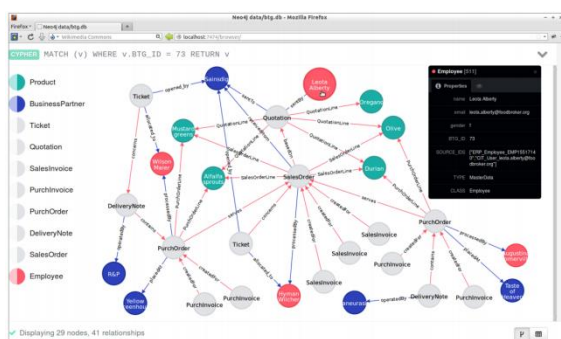


Figure 5 Relational graph visualization (Petermann, Junghanns, Müller, & Rahm, 2014)

2.2.3 Challenges for implementation

To implement an intelligence system, some information is needed. First, the available data sources are key for implementation. In order to establish a good intelligence system, the data sources that are available should be identified by establishing what sources are available, and what intelligence could be extracted from these data sources. The data sources should be divided in structured and unstructured categories, since this is the determining factor between intelligence 1.0 and intelligence 2.0. Next to internal sources, open sources should also be taken into consideration. Practitioners are aware of the potential of open data sources, although these sources are commonly not being used due to not adhering to being vetted as clandestinely- collected intelligence (which is therefore less creditable). Driven by time constraints and confronted by large amounts of information, practitioners focus their resources on analyzing clandestine-collected intelligence. This is said to be enhanced by managers who encourage this bias (Fleisher C. S., 2008).

The kind of intelligence determines the method for extraction, the kind of storage will be needed, and the method for data usage that will be used. The extraction method should be chosen based its possibility to extract the needed intelligence from the right source. The storage method should be chosen based on several aspects, such as the inclusion of historical intelligence (e.g. for comparison) or the need for multivariate intelligence. The method for data usage can be chosen based its ability to provide the right intelligence from the data. Knowing whether there is need for descriptive, comparative intelligence or intelligence after computerized analysis, is key to deciding this. Knowing what intelligence is needed is therefore essential for knowing how an intelligence system would look like.

Finally, it should be established how intelligence is to be presented. The intelligence presentation should be clear to the practitioners. Successful usage will only be established if the intelligence is presented in a clear way. Therefore, the practitioners can help in defining how they would like to have added intelligence (Watson & Wixom, 2007). Knowing the preferences of the practitioners is key in deciding what method will be used to present the intelligence.

This knowledge will help in deciding between the choices within each layer and define what an intelligence system would look like.

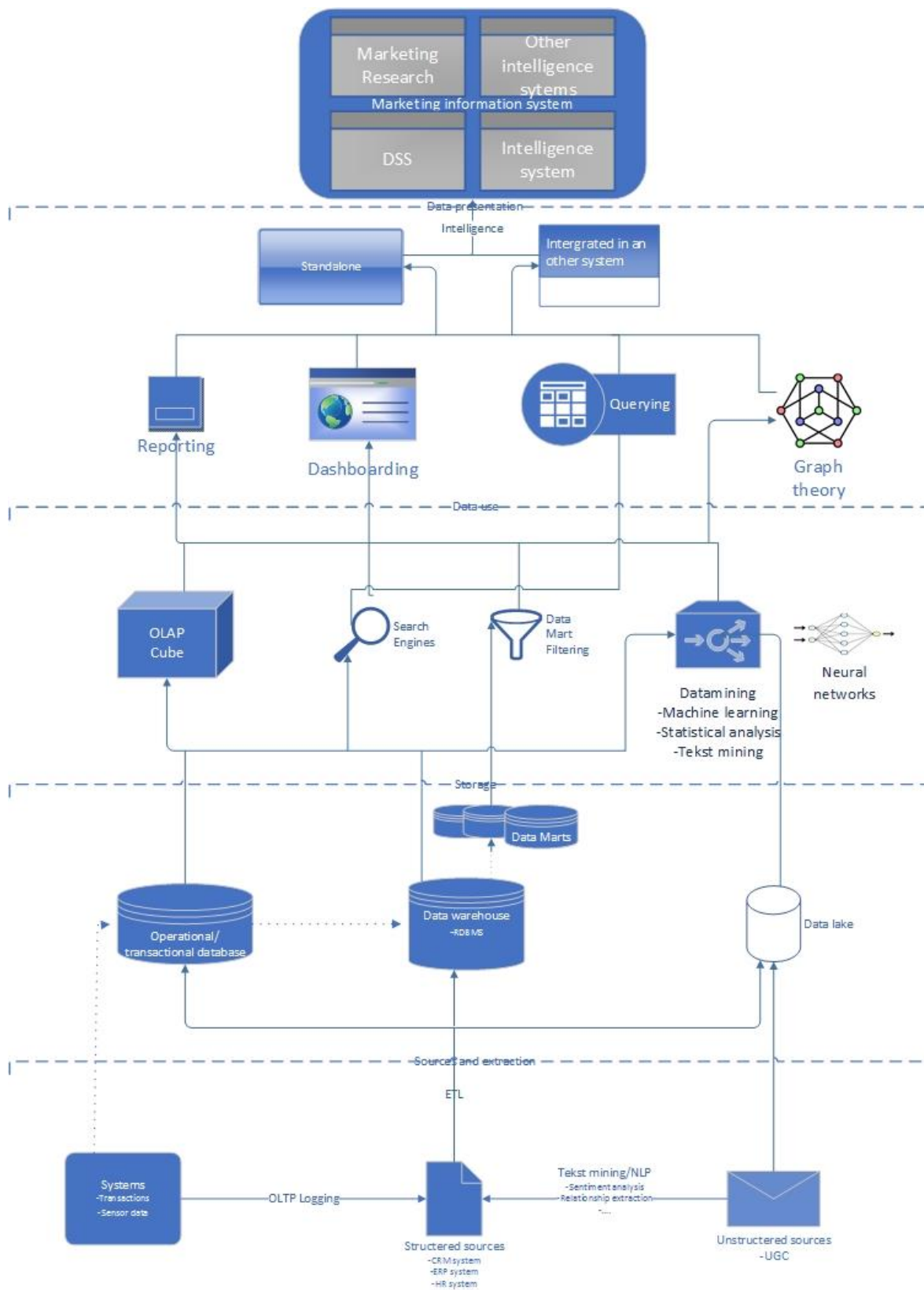


Figure 6 Framework with possibilities for an intelligence system

2.3 Finding the intelligence needs

A determining factor for the implementation of an intelligence system in the B2B marketing environment is having knowledge over the intelligence needs of the marketers. There is, however, a lack of literature describing how to extract intelligence needs. This lack of literature on the intelligence needs is generally regarded a bottle neck in marketing intelligence system design (Bose, 2008).

Practitioners are suggested not to have knowledge over what intelligence they need. As Vaskovits (2011) explained: “if you asked a person in 1800 what he likes to see better on transport it will result in faster horses” -- i.e., practitioners don’t know what is possible for them. Several reasons exist, why this might be also the case for B2B marketers. Wedel and Kannan (2016) explain that this could come from high variance in forms of intelligence in B2B marketing. Mauro, Greco, & Grimaldi (2015) add that -- next to high variety -- there is also very fast data suggesting B2B marketers can’t keep up with knowing what could be supplied. Due to these reasons, the value of intelligence drops leading to an overconfidence bias in B2B marketing that leads to market intelligence being seen as an expense instead of an investment (Bazerman & Moore, 2008). Knowing what practitioners need, can only be done by going further than asking what they need (McQuarrie, 2014). Therefore the methods of finding intelligence needs should be identified and reviewed to assess effectiveness.

A commonly used method to do so is the key intelligence topic (KIT) model. The KIT model identifies the intelligence topics that have the greatest significance for the practitioners. It provides purpose and direction (Herring, 1999). The model implies a set of specific questions that should state the intelligence needs of the practitioners. The questions should surround the “five Ws”: Who wants the intelligence, what intelligence do they want, when do they want the intelligence, where should they have the intelligence, and why do they want the intelligence. The questions of the KIT model, however, are based on the premise that the practitioners have a clear view of their own intelligence needs. The model also does not take into account the already available intelligence streams. This model can therefore ignore potentially important intelligence needs (Bose, 2008).

Based on the KIT model, identification can nonetheless be made on what the practitioners think they need. This is however just one of the potential gaps. Weiss & Wright, (2006) define the problem of this approach that it assumes the organization knows what it needs. This approach might therefore sideline certain needs.

As a solution Weiss & Wright, (2006) present an adaptation of the “Johari window”. This approach views organizations as learning entities that might not fully know their own needs and intelligence streams. The goal of such the window is to find the underlining needs of the organization, as well as provide a useful overview of the intelligence streams in place. The window they give four classifications of needs with knowledge: known known (open) intelligence, Known unknown (hidden) intelligence, unknown known (blind) intelligence and the unknown unknown (unknown) intelligence. Translating this to needs and information streams gives the following boxes. The open box clarifies already filled in intelligence needs. This box combines the known intelligence streams with the known intelligence demands to serve as an foundation for mapping the intelligence needs.. The hidden box clarifies the intelligence streams that are incorporated and not fulfill an intelligence need (i.e. the intelligence systems that are there but might not be used to their full potential, or might not be needed at all). The blind box clarifies what an organization knows it doesn’t know. Simply asking what is missing might not be the right method to clarify this since practitioners might not have a decent view of what could be possible. Instead mapping

both the needs and intelligence streams can help in clarification. Finally the unknown box suggests unknown needs that also are not filled with any intelligence stream. The unknown box is hardest to identify since it suggests examining all assumptions on intelligence needs and information streams on correctness. The goal of the Johari window is to minimize the blind and hidden boxes. An overview of the boxes is given in table 1.

By using the Johari window method for assessing the intelligence needs for practitioners, the assumption that the marketers might not know what they need is diminished. Instead of asking what is missing, the overall intelligence needs of the practitioner are determined and cross-checked with the already available intelligence streams to determine what is missing and what intelligence is provided, but too much. This method therefore also takes the current marketing information system into account. Even though this method still has a blind spot, it is suggested to be more effective than the KIT model (Weiss & Wright, 2006).

Table 1 Johari window: Needs and intelligence streams

	known marketing needs	Unknown marketing needs
Known intelligence streams	Intelligence streams that are used	Intelligence streams that are unused
Unknown intelligence streams	Intelligence streams that are known to be missed	Intelligence streams that are not know thus not missed

2.4 Summary

Marketing can be defined as “meeting need profitably”. To do so, accurate information is needed. Information needs can be derived in several themes surrounding Porters five forces model. There is, however, a difference between marketing towards consumers, and marketing towards other business. The consumer market is more volatile, and determined by a difference in distance to the customer. The way consumer relations are managed, and the different audiences targeted, suggests different needs. The intelligence needs for B2B marketers are not so well-defined in the literature. The marketing intelligence needs are fulfilled by the marketing information system. The marketing information system has several facets that provide marketers with intelligence. One of these is described to be the marketing intelligence system. There does not seem to be much research done to marketing intelligence systems, let alone on marketing intelligence systems for B2B marketers.

Intelligence systems overall come in several variants. Early intelligence systems emphasize the management of available knowledge such as Human knowledge like using the sales force, and knowledge from simple structured sources is explored by mainframe based systems. It doesn't use analysis, and is dependent on availability of data and willingness/ability to share knowledge. Current intelligence systems are much more elaborate than this. With the recent addition of so-called intelligence 2.0, a wider field of sources becomes available, and data mining techniques makes different types of analysis possible.

In order to determine how an intelligence system would look like, several aspects need to be known. First the available data sources need to be known, including their structure. Second the desired intelligence should be known and some aspects of this intelligence. Does the intelligence suggest a need for real time intelligence and need for comparing with other time zones? Does the needed intelligence entail predictive, prescriptive or descriptive intelligence? Can the needed intelligence be extracted with the current tooling? Finally, the preferred method for presentation should be established to increase its usability.

Finding the intelligence needs and gaps in the B2B marketing information system should establish what kind of intelligence is needed. By using a Johari window it is possible to find gaps in the information system with regard to intelligence needs of the B2B marketing practitioner. By questioning practitioners on unused sources and potentially valuable sources, grip can be gotten on potential intelligence sources that could be used as source for the intelligence system. An overview of the research is given in figure 7.

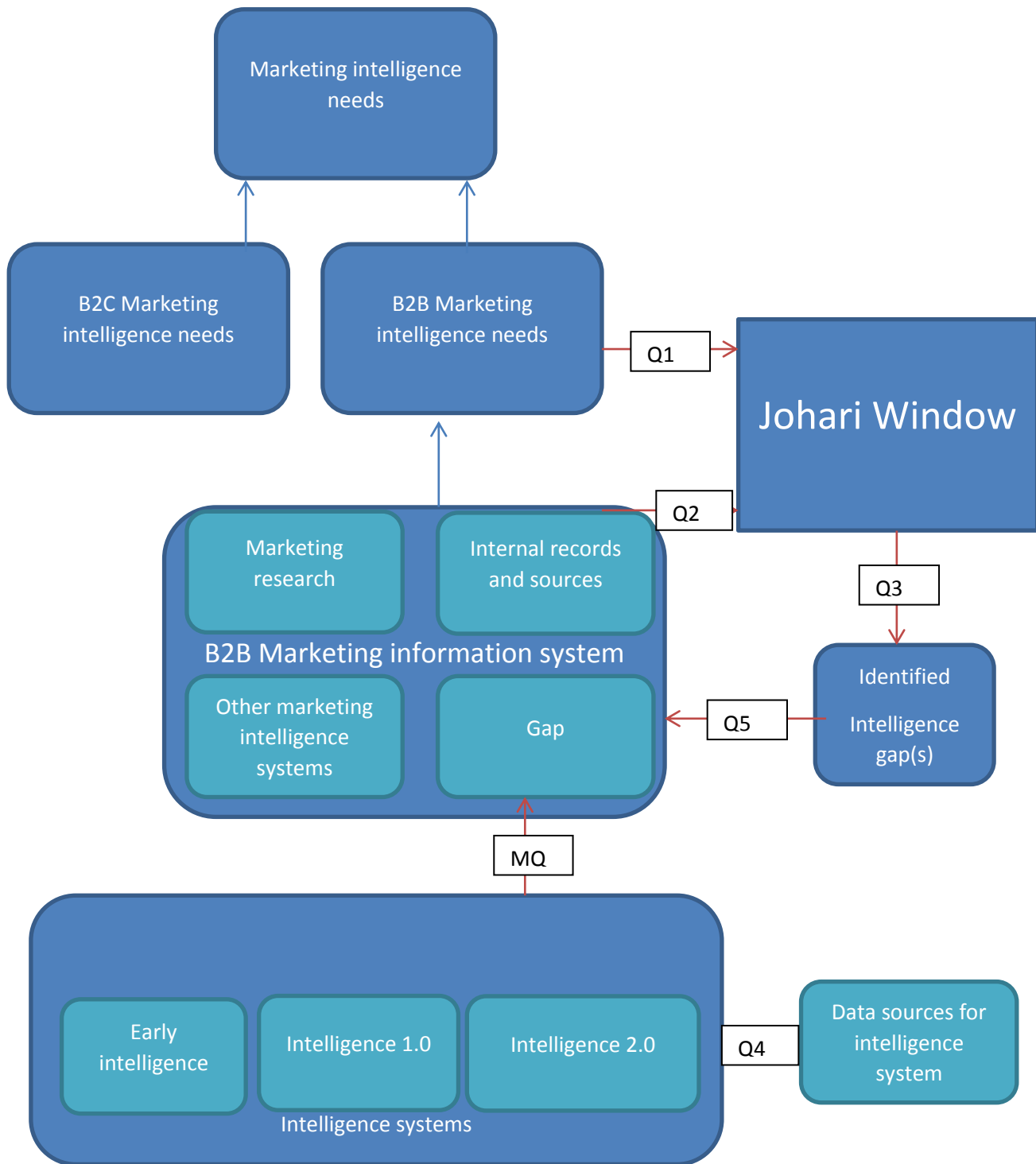


Figure 7 Conceptual framework for data extraction

3 Methodology

This chapter will explain how the study will be performed. It will go into detail on what data will be collected, and which methods will be used for analyzing that data. Section 3.1 will describe the research and justify why the choice was made to go for a qualitative case study approach. In Section 3.2, the case study for this research will be explained in greater detail, together with the case study approach. Section 3.3 will explain three distinguishable phases of the research strategy: the preparation phase, the collection phase and the analysis phase. Section 3.4 will present the validity and generalizability tactics of this research. The chapter ends with a summary.

3.1 Justification

For this research a case study design was used. The use of such a design can be justified from a theoretical perspective and from a practical perspective. This subsection will discuss both perspectives.

Theoretical justification

Research in general should try to fill a knowledge gap. For this research specifically, this gap is about how an intelligence system would look like for B2B service applications. The literature shows that there is knowledge on how intelligence systems look like, although it lacks information and detailed knowledge on how this could be implemented in the B2B market.

The choice of research design should thus be focused on filling this gap. To give a clear overview of what kind of information is needed, the main question of the present research is:

How should an intelligence system look like to effectively add to the B2B marketing information system of an IT solution consulting company?

As was reviewed in the previous chapter, the existing literature provides enough knowledge on intelligence systems, however lacks specific knowledge on applications in a B2B marketing setting. The emphasis is thus on B2B marketers.

The findings of this research will add to a field in which not much previous research is done. Exploratory research is advised when not much is yet known, not much information is available or when similar cases are missing (Sekaran & Bougie, 2010). Exploratory research designs are specifically defined as the process of gathering valuable information through informal or unstructured manner. This is advised when not much is yet known on the area (Burns & Bush, 2010). Given the scarce literature on B2B on the research topics, this research, therefore, has an explorative nature.

The case study methodology is mentioned to be specifically useful for research questions regarding exploratory research (Yin, 2014). Case studies involve in-depth contextual analysis of matters in different settings within the scope, and are especially useful in understanding certain phenomena and gathering further theories (Sekaran & Bougie, 2010). Furthermore it is flexible enough for studying new technologies (Yin, 2014).

Practical justification

The study is performed for the professional services and consulting firm Capgemini. The question raised by the marketing department was how the current technological advancement could aid in marketing, specifically the B2B marketing approach used by Capgemini. This was eventually scoped towards technology providing intelligence or intelligence systems.

For this research, the researcher was able to generate an in-depth understanding via an internship at a professional services firm. The researcher was able to be among the marketing team at the sponsoring firm. This gave the ability to observe the doings of marketers and to talk to them about the problems and success factors in their daily work. Easy access to the whole marketing and communication team enhanced the possibility to derive in-depth qualitative information, which made a qualitative approach more valuable.

The case company was a suitable setting for studying the intelligence systems for B2B. Due to the firm's size, it is able to apply a holistic marketing approach in which several approaches to B2B marketing were

being utilized. The firm made it more generalizable towards B2B marketing, whereas (multiple) case studies only looking at one approach to marketing might not have strong evidence towards B2B marketing as a whole, but more specifically to the studied approach.

Aware of technological advancements, a case study design can help clear this up for the sponsoring firm as well as adding to filling a literature gap.

Research question

The combination of identified knowledge gaps, the research question and the opportunities given by the case firm led to the following questions.

In order to answer this question, the B2B marketing information system should be examined in order to find out how an intelligence system could add useful intelligence. The needed intelligence should be examined to make choices for the intelligence system. Specifically:

What are the overall intelligence needs of B2B marketers?

To determine how an intelligence system would look like, several aspects should be known about the intelligence gap: whether it includes the need for historical data, whether the intelligence provides descriptive information or analysis and whether the intelligence can be extracted with the current available tooling. The intelligence system will thus have to use sources able to extract the intelligence from. These sources should then be examined to make choices for the intelligence system. Specifically:

What data sources are available for an intelligence system?

Finally the intelligence system's success depends on the usability and understandability of the intelligence. Knowing how the marketers want the intelligence to be presented can help in making it more easy and understandable.

How would B2B marketers like the intelligence to be presented?

3.2 Case study design

Several forms of case studies exist, as reviewed in Yin (2014). Next to single case and multiple case studies, Yin also describes holistic case studies, in which the case is researched as a whole, and embedded case studies where multiple units of analysis are identified. The latter is described to add breadth and depth to the data. This present research will focus on a single embedded case study with multiple units of analysis. The sponsoring firm is used as the case firm. Within the sponsoring firm several general approaches to B2B marketing are used, and each of these approaches will be taken as units of analysis. The case study approach is visually summarized in figure 8.

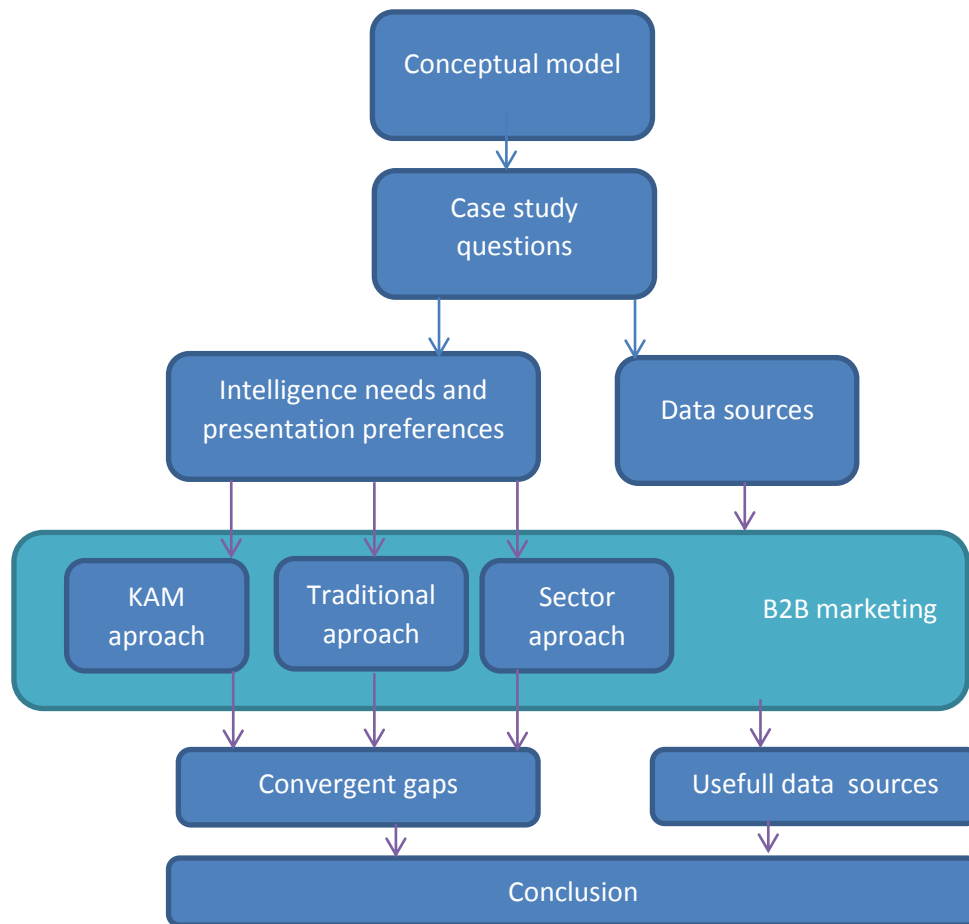


Figure 8 Visual summary of the case study approach

General B2B marketing approaches

Each unit of analysis has to be treated similarly. The strength of using several units of analysis comes from the ability to find converging evidence. Each case should therefore be researched the same way, and the outcomes of the study should implicate the same results. In this research, three constructs are opt to be found: the intelligence needs, the presentation preferences, and the potential data sources. Data sources are not seen to be case dependent and can therefore be collected across all cases. The units of analysis are: sector approach, the traditional approach, and the key account marketing (KAM) approach. Each approach will be shortly described. How the units of analysis link together can be read in appendix F.

Sector marketing managers (Sector approach)

Sector-based marketers are responsible for pursuing marketing actions towards their given sector or group of customers. They are tasked to target these clients with the whole variety of products and services that the company has to offer. How they fill this in is dependent on their own beliefs. So can marketing for instance be pursued through an app or by mailing updates and newsletters. Their main activities involve marketing planning, pursuit marketing, corporate events, and external communication. Pursuit marketing can be defined as pro-active and supporting marketing activities to look for possible opportunities. Therefore, close contacts with customers is of importance. Sector marketers are thus responsible for the marketing activities toward specific clients. Knowledge about these clients could help

in pursuing better and more targeted marketing. The marketing managers might also have a view on what data sources are / should be available for implementing such a system.

Service/product marketing managers (traditional approach)

Service or product marketing managers have a job description similar to the sector marketing managers. However, they focus on a specific product or service that needs to be marketed. Their client area is therefore very wide. As the market keeps moving, these themes are subject to ongoing change. Also, the services are very closely related, and often a single opportunity involves multiple services or products. The services might sometimes also be marketed to an account pursued by the sector managers.

Account executives/key account marketers (KAM approach)

The account executive is responsible for the acquisition and development of clients within a given account. Their focus is on enhancing the revenue streams at their already existing customers and hunting for additional contacts with potential growth of network. They are doing this by building relationships with the purpose of selling the broad service and product portfolio. To do this, they must find and identify the needs of the customer. They thus are knowledgeable about the market and aware of the trends and developments in the market. They are potential end users of the intelligence system and they might have knowledge on which data sources and streams are useful for future implementation.

3.3 Research strategy

This subchapter will discuss the research design. As dismissed at length in Yin (2014), the research design can be subdivided in three distinctive phases with the goal of answering the questions raised. First a preparation phase is introduced. The formation of the topic list for information extraction is explained by two directions. The second phase is described as data collection phase, in which an explanation is given as to how the qualitative data is collected, what structure is used, and how the elements for extraction are chosen. The third phase describes how the extracted data will be summarized and analyzed. Attention is given to the use of specialized software and a second coder. Each phase will be discussed in the following subsections.

3.3.1 Preparation

The goal of the preparation phase was to construct the topics posed in the interviews. Two directions were taken to come with the topic list. The first form of preparation came in the form of getting familiar with the studied environment. In this research, the case was represented by the sponsoring firm's marketing department. Second, the theoretical preparation involved doing a literature study towards the research subjects to come up with a research model, and to identify the knowledge gaps that needed to be researched.

In order for the researcher to conduct good explorative research, familiarization was needed. Getting to know the jargon and people and systems could help. Not only did this help with making the data collection more understandable for the employees, but it also resulted in the researcher being able to better comprehend the answers. Several forms of data were available to the researcher. The researcher had introductory interviews to get familiar with the marketers, attended marketing meetings and observed the employees. Furthermore, the researcher had several forms of documentation available, read through the intranet and accessed and used several of the corporate information systems. In other words, the researcher had access to a large number of primary and secondary data sources, and also was

capable to directly observe participants in the case company's department. An overview of the preparatory sources available is given in table 2.

The second preparation direction to establish the topic list came from desk research. The literature review (see Chapter 2) constituted a model of information needed to determine what an intelligence system for B2B marketing would look like. The model set the scope to the topics to be extracted from the marketers and functioned as a benchmark for the interviews.

These two preparatory phases helped in the construction of the open ended case study questionnaire that were being used in for data collection the employees. By identifying what data was needed, and being able to convert this requested knowledge into questions that would be understood by the employees, a good and understandable topic list was made; see also in appendix A.

Table 2 Research data

Data source	Accessing method	Form	
Documentation	Content examination	Several internal documents and the intranet	The researcher was able to access the internal documentation of the firm by means of accessing the intranet. This documentation came in several forms under which reports, presentations and internal findings. Because the overwhelming amount of documentation, the researcher went through the documentation selectively.
Individual employees	Introductory interviews	Introductory interviews	Introductory interviews were held with the purpose of getting familiar with the employees. This ensured more comfort during later phases, and made it possible to determine the relevance of the employee.
	Participant observation	Observation	Observation of marketing and department was done by mean of attending marketing and sales meetings and observing their day to day activities.
Available systems	Observation	Observation of the most common intelligence tools and systems	The researcher was given access to or was shown several tools and systems internally. These systems gave the researcher a basic understanding on the available information system. Understanding this prohibited extensive explanation during data collection.

3.3.2 Data collection

The employees of the case company were the main source for information; although in order for the data collection to run smoothly, the method for data collection, the structure for getting the data and the method for selecting employees, had to be determined.

Method for data collection

The method for data collection resulted logically from the case study approach. Focus groups (group discussions on topics), standalone open interviews (one on one discussion on topics) and surveys (listed specific questions) were considered. Surveys were not deemed to be flexible enough to extract the right kind of information since in-depth information is needed that suggest follow up questions. The busy time schedules of the marketing employees made focus groups a hard/impossible task. Therefore interviews were the most viable option for data collection.

To stimulate the marketing and sales employees to include the possible demands coming from tacit knowledge, semi-structured interviews were held. The semi-structured approach combines the rigorous format combined with openness to allow new ideas to be brought up and gave room for possible further explanation of demands that come forth from tacit knowledge. Semi-structured interviews hold two important requirements. First, they are well suited for the exploration of the perceptions of subjects regarding complex and sometimes sensitive issues and enable probing for more information and clarification of answers. Second, the varied professional, educational and personal histories of the sample group precluded the use of a standardized interview schedule (Barriball & While, 1994). The semi-structured interview gives the interviewees choice in working to their answers and the use of probes, which made it possible to explore sensitive issues (Hutchison & Skodol-Wilson, 1992).

Structure for data collection

To gain as much knowledge as possible from the respondents, the interview process followed the consecutive steps as described by Spruijt (2016) and shown in figure 9. The following steps were taken to ensure the right information is received from the interviewees. Profession title was used to select the interviewees (the right candidates that could shed light on the wanted topics). Practical agreements were made with these candidates, including time, location, length, and agreement on the interview being recorded. Afterwards, the interviews were conducted and transcribed and sent to the interviewee to be checked. This was followed by a content analysis of the transcriptions and processing the results for this research.

The choice was made for denaturalized transcription (Bucholtz, 2000) to retain as much information as possible. Since making transcriptions can be a long and extensive task, these were made using the AI powered services of Trint. This service translates audio files to text. Since this service might make mistakes, the researcher has gone through the transcripts and fix errors manually.



Figure 9 Interview process (Spruijt, 2016)

Sampling

The interviews were structured towards the employees working in B2B marketing. These marketers were thus the population for sampling. Within this population, each employee was a single element within their respective unit of analysis. Because the marketing department of the firm contained an enormous number of marketers, sampling was required. Because the researcher did not have a complete list of all the employees, probability sampling couldn't be used (Sekaran & Bougie, 2010). Therefore, in this research, non-probability sampling was used.

The researcher was dependent on the availability and willingness of the employees to volunteer in the research. Especially the employees using the KAM approach were extra busy. Therefore, for this research convenience sampling was used -- by sampling the elements that are most easily reached, a higher number of elements could be sampled. The researcher was aware of the potential bias of the sampling technique and the possible insufficient power to identify differences in the population; however for the explorative research the advantage of being able to interview more people outweigh the disadvantage.

A total of 11 employees were interviewed in all of the pre-given units of analysis: the sector-based marketing managers (N=4), service-based marketing managers (traditional approach) (N=3), and account executives (KAM approach) (N=4). Each interview was conducted using a semi-structured approach with the help of the pre-developed case study questions. The employees were allowed to discuss freely, in order to extract more (useful) data from them. Due to the researcher having background knowledge in the field, explanation of systems and terminology was not needed, which resulted in a more fluent discussion.

3.3.3 Data analysis

Due to the qualitative type of data that was derived, the data lacked an obvious structure. This is however typical for data gathered from interaction with people (Mortelmans, 2013). The data therefore had to be processed to get useful information out of it.

Coding and analysis

Due to the extracted data lacking a useful structure, it became hard to see links and extract useful knowledge out of it. Sekaran & Bougie, (2010) in such circumstances suggest processing the enormous amount of data using data reduction technique called coding. Coding would help to make it easier to draw meaningful conclusion from qualitative data. After the interviews were transcribed, the interviews are coded and analyzed.

Coding procedure

For this research a combination of open and selective coding was used. The interview transcriptions were first open coded. All information that in the interviews that had any form of knowledge was coded. The coding structure was divided between the units of analysis. Recurring codes within a unit of analysis could therefore be merged together.

After all transcriptions were coded, the codes were placed in groups surrounding the question topics. For the purpose of grouping codes together, thematic codes were added to the code set with the captions of the topics. Within the groups, linkages and themes were sought, and concept maps were formed (Daley, 2004).

Codes that could not be placed within an group were collected for identification of overlooked topics. This resulted in serendipity, finding related sub-topics to information needs and current information system, and finding a topic on the profession of the employees. These codes were mostly explanatory. Codes that did not belong to any of the topics were deleted.

After the topics were found, selective coding was applied. The researcher went through the transcripts again to find knowledge that belonged to the topic but was overlooked.

By doing so a list was made of 270 codes within the several topics and units of analysis. After all the codes were categorized, linkages between the codes were sought. This resulted in getting a clearer overview of the various branches within each topic category.

Analysis

To answer what the intelligence need were of the marketers, gaps should be sought between the information supply and the information demand of the marketer. As mentioned in the literature study (in Chapter 2), the researcher aimed to use the Johari window to extract the intelligence gaps. The information needs for each unit of analysis were plotted against the information the current marketing information system provides. Linkages were made between these to show fulfilled information needs. In doing so, gaps have become visible. The information needs without link were unfulfilled.

After finding the intelligence need that is not backed by the information system, all information on that specific intelligence need is gathered by using the connected linkages. When all information on that intelligence need is gathered, the researcher tried to answer the questions to determine what kind of

intelligence system should be useful. The intelligence needs were then cross-checked against the available sources to determine whether these contained the information needed.

Atlas TI

To analyze the transcripts, the software package Atlas.ti was used. Atlas.ti is qualitative data analysis software that will give the researcher the ability to organize categories and visualize the data that is obtained from the interviews. Atlas.ti is not subjected to a specific coding strategy. It allows the researcher to organize the access to information. It will show the themes and subjects of the interviews using graphics in the form of webs. This would enhance the researcher's transparency, and show the thoughts of the researcher. Color schemes were used to make the visualization easier to understand and to divide themes from each other.

Atlas.ti set the possibility to produce families in which documents could be placed, and families in which codes could be placed. Filtering could afterwards be used to show only a specific set of documents or codes. The researcher used these capabilities to disperse the codes and transcriptions of the several units of analysis. In doing so the researcher was possible to research each case in isolation.

The Atlas.ti tool gave the researcher the ability to check how often the code appeared. It showed this number as the groundedness of the code. For this research, however, the groundedness of the codes was neglected, since no claims could be made based on this number.

Second coder

Hutchison & Skodol-Wilson (1992) explain that the use of semi-structured interviews can lead to the use of specific wording and probes, which can result in lower reliability. To ensure some objectivity, a second researcher was asked to code one of the interviews. Since the coding process is subjective in nature, decision was made for a second coder who would code a random chosen interview (Mouter & Noordegraaf, 2012). The second coder was asked to perform coding independently. These results were compared with those of the main researcher. The two coding structures of the same data would be followed up by discussion leading to a more valid analysis.

The second coder went through over 9% of the collected interview transcripts, which comes close to recommendations for second coding (Lombard, Snyder-Duch, & Bracken, 2004).

The second coder was given a transcription of a random interview. This coder was told about the topics in the form of the research objectives for this research, and was asked to code the interview towards finding possible answers to these objectives. Reliability coefficients were measured as to how much the data deviated from perfect reliability. This is done by calculating the percentage agreement. As stated by Riffe, Lacy, & G.Fico (2005) an appropriate reliability score was said to be above .667. The test for the present research suggested a reliability coefficient of .722. The determination of this score is given in appendix B.

The lessons learned from the discussion afterwards were incorporated in the coding strategy of the rest of the interviews.

3.4 Validity and reliability

The quality of scientific research is determined as objective and universal; it states that the subjectivity of the researcher may not play a role in collecting and analyzing the data and that the outcome should be universally applicable (Mortelmans, 2014). Therefore, the quality concerning the choices of methodology should be discussed.

Due to this research being a single firm case study, it offers lower grounds of external validity (Yin, 2014). Due to it being a qualitative study, the research is more subject to bias from the researcher. There are some measures taken to increase the quality of the research. These can be subdivided between increasing internal validity, construct validity and generalizability.

Internal validity

Internal validity is ensured by the researcher first getting acquainted with the terminology using documentation and observation. This ensured less misunderstanding when collecting, coding and analyzing the data. The graphical mapping scheme for analyzing the data further structured the analysis method.

Construct validity

Several tactics are used for maintaining construct validity. First the research of a multitude of employees is used. The knowledge thus came from different sources. Secondly the use of multiple coding schemes ensured all the relevant information to be used. The inclusion of a second coder to determine inter-coder reliability proved that the right information was extracted.

External validity

External validity is established by using interviewees being employed as different functions under the umbrella term of B2B marketing. This established the interviewer to obtain multiple views on the topic.

3.5 Summary

The research was executed as a single case study within the sponsoring firm with the use of multiple units of analysis being the different approaches to B2B marketing. Before data collection, the researcher used several forms of data to become familiar with the terminology and systems in the firm. The information from the literature review, together with the researcher being familiar with the research environment, resulted in a topic list for data collection. The data was obtained with the use of semi-structured interviews with volunteering B2B marketers. The interviewees were chosen on the basis of convenience sampling. The data was coded using specialized software. Open coding was used for summarization of the transcripts, codes were linked and collected under the predetermined topic categories, after which selective coding added to these categories. Inter-coder reliability was determined to prove validity. Categories were then linked together to determine the information gaps. The gaps were cross-checked against the sources to determine if the sources contained this information.

4. Research findings

This chapter will discuss the research findings. The objective of this chapter is to answer the second sub-question:

What are the overall intelligence needs and preferences of B2B marketers that can be met by an intelligence system?

A total of 11 in-depth interviews were performed, coded and analyzed. These interviews covered all units of analysis within the case. In this chapter the findings from this analysis will be discussed. In section 4.1 all topics will be discussed for each unit of analysis, together with the analysis of linking the information needs to the supply of information to identify the information gaps. Section 4.2 gives all the sources stated in the interviews, including what information could be extracted from them, what structure the source comes in and how it can be extracted. The chapter will end with a conclusion of the findings.

4.1 Units of analysis findings

In this section the findings about the units of analysis are given. For each unit of analysis I will start with describing the function of the marketing approach the unit of analysis represents as given in the interviews. Furthermore, I will provide the information needs for their function, describe the information system currently in use, and show the analysis towards the intelligence gaps. Finally the functional presentation preferences will be discussed.

4.1.1 Sector based marketing (SBM) managers

The sector-based marketing managers provide marketing activity toward a set of specific customer accounts (i.e. customer companies the specific marketer focuses on). Their role consists of two major concepts. They are responsible for branding the firm towards these specific accounts, and finding and producing opportunities within these accounts. They describe their specific customer accounts as individual markets in which they try to market their services. They do this by working as close as possible with the client by means of contact and marketing campaigns. The marketing campaigns are mostly executed by emailing the client and by organizing events to show the company brand or show the benefits of a specific service. This all is done to produce and find opportunities for these clients that can be nurtured by the sales department to sell the specific service. An overview of the codes and linkages between the codes toward the function is presented in appendix C.

The needs for SBM

The sector based marketing manager tries to market the firm's services towards their focus accounts. They do this by finding and creating demand. They focus on finding information by doing research, having discussions with the client, and puzzling the information pieces together toward finding the right demand. The theme that clearly emerges from the interviews is the need to understand the account. Four categories are found on understanding the accounts: (1) knowing their vision, (2) knowing their competition, (3) knowing the structure, and (4) knowing the people who work in the account. The latter two can again be subdivided in several forms of information.

The marketers identified several forms of intelligence they would like to collect about individual people working in the account: roles, hobbies, professional relationships, activities and interests. First, knowledge of someone's role can strengthen the marketers in framing the marketing proceedings towards helping the stakeholder. Second, knowledge of someone's hobbies could possibly increase targeting. Messages could be personalized using hobbies to be received better. Knowing about their personal relationships, could be used to influence a whole network instead of only the main stakeholder via indirect targeting. Finally, information about someone's professional interests and activities can be useful, as this can help the marketers to target their clients better. As an remark, the marketers mentioned that intelligence on individual people needs to be up to date to be usable in their marketing campaigns.

Several forms were also mentioned for knowing the structure and especially a clear view of the stakeholders and how they are connected. Firstly, the marketers showed interest in knowing what subset of people working within an account is part of the decision making unit (DMU) for implementation to have more focused targeting. They were interested in knowing how linkages between people within an account are changing so the right message is send to the right people. Furthermore, the interviewees were looking to identify the most influential stakeholders within an account -- to more

efficiently run an indirect marketing campaign. Finally, they wanted to broaden the current scope of people they have listed within the account. The concept map of the intelligence needs can be seen in Figure 10.

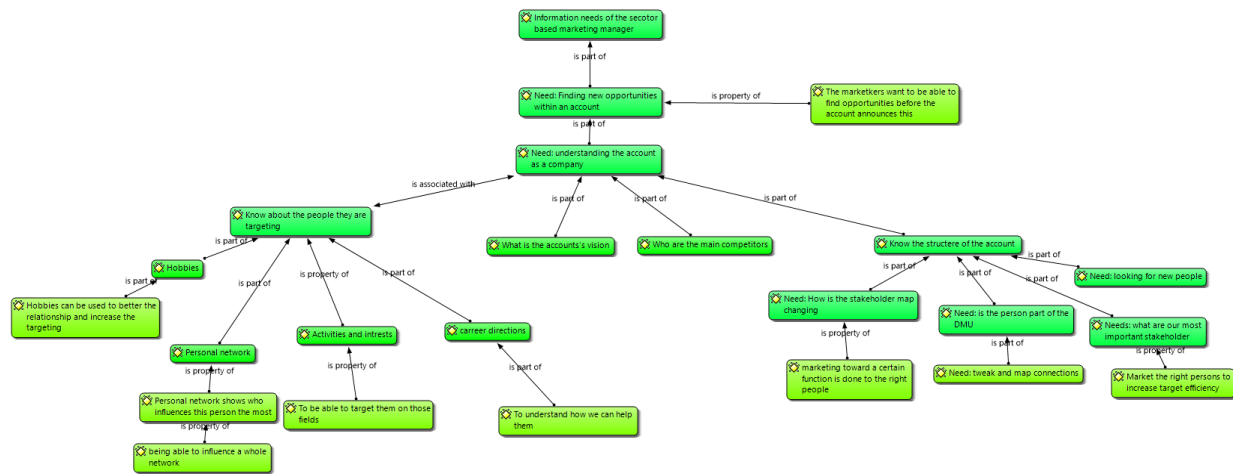


Figure 10 Concept map intelligence needs SBM

SBM information system

Figure 11 offers the concept map of the intelligence streams that were mentioned in the interviews. It shows that the intelligence streams available to the sector based marketing managers can be subdivided in two categories: (1) the informal streams, and (2) the formal streams. The informal streams can be understood as intelligence streams that were not recorded for future reference. In other words, they provided a more tacit form of knowledge about the accounts (Newell, Robertson, Scarbrough, & Swan, 2009). This category contained several forms of information streams: First, they consisted of discussions with the implementation team working for the account and on site of the account, which enabled the manager to know what the client was talking about off-the-record. A second stream came from informal surveys conducted on site. Questions like “what are the ambitions of the company?” and “how do you see the firm?” were asked to get a better view of the position of the firm. Finally, the bigger accounts also had sales employees and engagement managers working on site. These employees provided the marketing team with rich insights into what was happening at the account, and into the topics and themes posted on their intranet.

Formal streams contain more codified knowledge (Newell, Robertson, Scarbrough, & Swan, 2009). According to the interviews, this is how the marketers got notifications on news posted about their accounts. For big accounts these were said to be “a bit overwhelming”. They also got information on the account by visiting that account’s specific website, on which information could be gathered on several topics. Finally, external parties brought out research on the market that included their specific accounts. A big part of the external research is done by analyst firms. For specific information, desk research is used. Desk research comes in various formats: Social media followings for instance give the marketing managers a sense of what is going on at their customers. This source of knowledge, however, is not offered in a structured way. To find the more relevant information, the team must dig deeper on the internet. Because of a lack of time, this is usually done by the team’s researcher, who summarizes the key findings in a report. Interviewees indicated that this however took time.

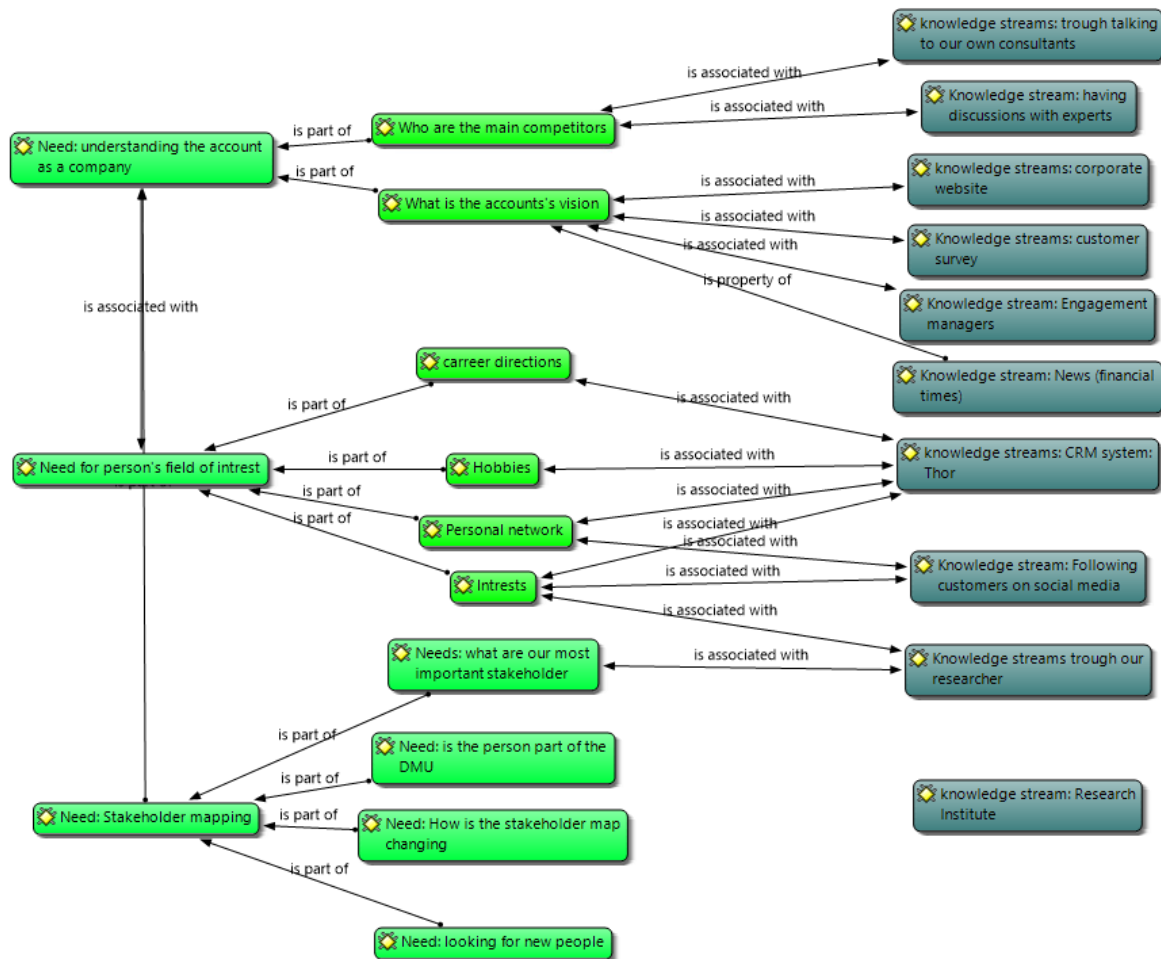


Figure 12 linkages intelligence needs and streams SBM

Presentation preferences

The sector based marketing manager's stated three preferences for an intelligence system with additional intelligence: (1) It should have a search function to be able to go through the given intelligence; (2) It should be linked to the CRM system to have the information available on a central location, and (3) because of time constraints, the information on offer should be presented in brief form (an overview of the codes is given in appendix C).

4.1.2 Portfolio based marketing (PBM) managers

Portfolio marketing managers are responsible for the marketing of a specific service (or portfolio of services) towards a wide range of customers. They do this by building and proposing marketing initiatives and campaigns surrounding their portfolio. Next to that, they are also responsible for the brand(s) in their portfolio and the generation of opportunities within their customer range. An overview of the codes and linkages between the codes toward the function is presented in appendix C.

Needs for PBM

The intelligence needs of the portfolio marketer can be divided in two components: (1) they wish to be up-to-date on the latest trends in marketing (and pursuing marketing); (2) they wish to (come to) know the customer. Being up to date with the latest trends in marketing will help the portfolio marketer to propose and build more efficient marketing campaigns. The need to know the customer comes from their desire to make the marketing message stick better, and to develop more targeted marketing communications, even trying to scope down to the person (I.e. personalization). The interviewees referred to this as “1 to 1 marketing”.

Within the category ‘knowing the customer’, several forms of information needs arise. First, the interviewed marketers expressed an interest in knowing the challenges that are playing at their customers. They believe that knowing more about this could help in producing better and personalized solutions. Second, they wanted to know the interest of the customer for more personalized messaging. Third, they wanted to know whether the person is part of a DMU to be able to specify their target scope. Further, they displayed an interest in the activities the customers were engaged in, both for speaking and participating, because this would offer insights into how personal marketing can be pursued through their own employees. Finally they showed interest in knowing the contact details of the customers so as to be able to follow up on them. The concept map of the intelligence needs can be seen in Figure 13.

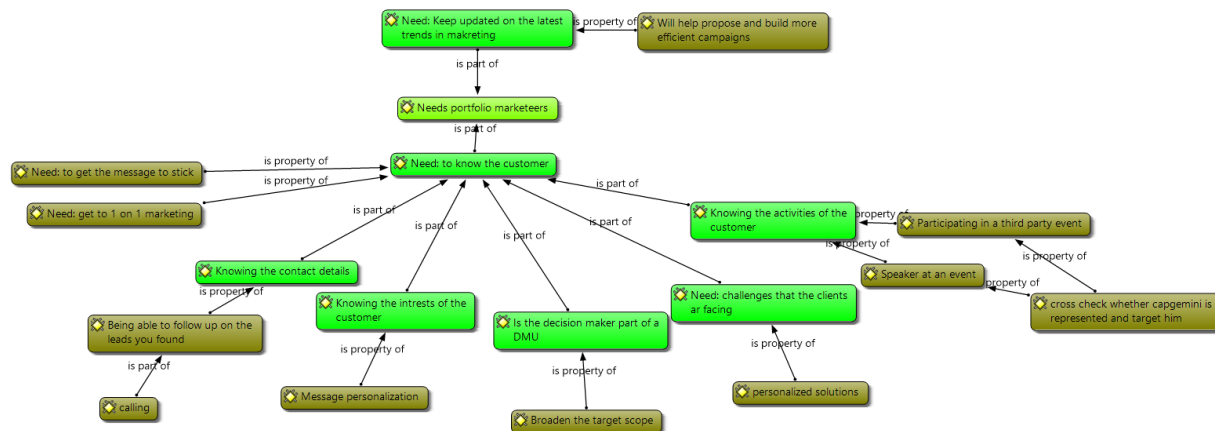


Figure 13 Concept map intelligence needs PBM

Knowledge streams for PBM

Portfolio marketers rely on streams of information to market their portfolios. Several forms of information are described by the marketers: most prominent are the sales people. The sales employees walk around on site of the client and have close contact with potential customers. They thus collect a lot of tacit knowledge about the client (e.g. knowledge on who to invite to events). Although these employees are transparent, they are dependent on what the customer shares with them. Knowledge coming from a sales person is indirect, thus might be biased. Second, portfolio managers use analyst reports as source of information about the latest trends on several topics. Such reports give an averaged out view of the current challenges of companies as well as the latest trends in marketing. Third, annual reports and resource reports from customers were mentioned as an information source to give marketers insights in what is coming from customers and what direction they are taking. Finally, portfolio managers mentioned the marketing researcher as source for on-demand information. The

marketing research was however perceived as indirect and providing specific and narrow information. The concept map of the intelligence streams can be seen in Figure 14.

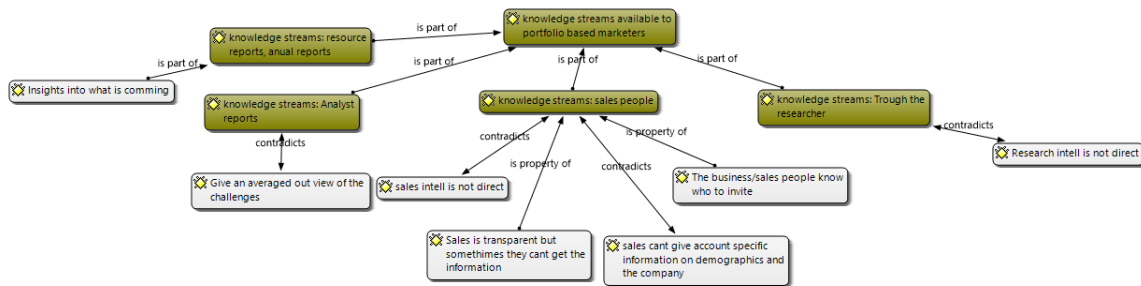


Figure 14 Concept map intelligence streams PBM

Intelligence gaps PBM

Figure 15 visualizes the match between the demands of the portfolio-based marketers and the already available information streams. All information demands of the portfolio marketing managers can in some form be fulfilled by their information system. It should however be noted that this comparison does not take into account some downsides to the information gathered from sales people (due to bias, availability and transferring information) and the researcher (due to adhering to marketing research instead of marketing intelligence, and thus providing narrow and on demand intelligence). These downsides suggest that there is still an intelligence need for knowing the customer's activities, interests whether they are part of a DMU and their contact details.

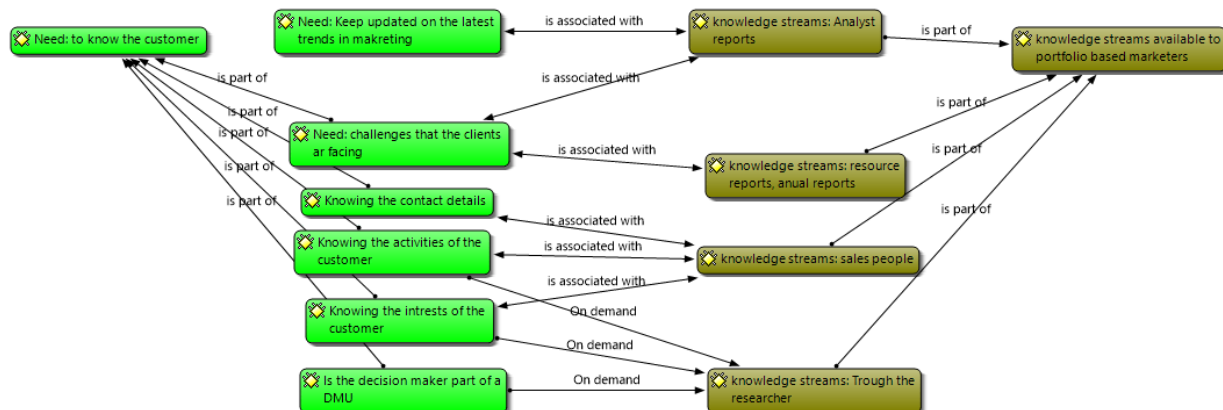


Figure 15 linkages intelligence needs and streams PBM

Presentation preferences PBM

The marketers stated two preferences for an ideal intelligence system that would provide additional intelligence. First, the intelligence should be integrated in the CRM system. They mentioned to be overwhelmed with tooling and suggested it might be used more if integrated within the platform. Second, they would like to have an easy to use system (an overview of the codes is given in appendix C).

4.1.3 Account executives/key account manager (KAM)

The account executive manages the account team that focuses all efforts towards an account. Three major themes were mentioned for this function: (1) as the head of the team for a specific account, the account executive represents the firm toward the account. All activities regarding the firm and the account therefore go by the account executive. (2) The account executive is responsible for fetching business within this specific account, and should be up-to-date on the happenings within the account. (3) The account executive is responsible for getting the right margins for the firm. The account executive thus needs a lot of information on the account for efficient performance. An overview of the codes and linkages between the codes toward the function is presented in appendix C.

Needs for account executives

In order to fulfill the function of account executive, several forms of information are needed: (1) information on the account, (2) information on the sector, and (3) information on the people working within the account. The account executives stated the need for information on relevant ideas within the sector, which could be used as cases within their own account. Trends in the sector and information implying change were said to be useful.

Information needs on the account came in several forms. First, interviewees mentioned the need to know about the ambitions of the account. This could help them prepare for potential tenders, and increase the chances of winning deals. Second, the interviewees stated that they wanted to understand their accounts. Introspection could then help in finding potential opportunities. Further, they wanted to know about the latest trends and be up-to-date on knowledge about the account. This would increase chances of finding potential opportunities early on, and increase the preparation time. Finally, interviewees stated the need for being up-to-date about projects at the accounts. Especially end-dates could help in knowing when renewal of projects could be announced, and when opportunities might appear.

Information needs about the people working in the account also came in several forms. Interviewees mentioned the need for knowing what drives people outside the business. This could be used to strengthen relationships, and to target them more efficiently within the boundaries. They further mentioned the need to know all stakeholders and their roles, so as to be able to contact the right stakeholders. Finally, interviewees mentioned the importance of knowing the stakeholder map and who is in the decision making units for projects to influence them before tenders take place. This is especially important, since most tenders prohibit contact with the decision making unit. To be effective in their marketing efforts, the account executives mentioned that the need for up to date intelligence about people working in the accounts. The concept map of the intelligence needs can be seen in Figure 16.

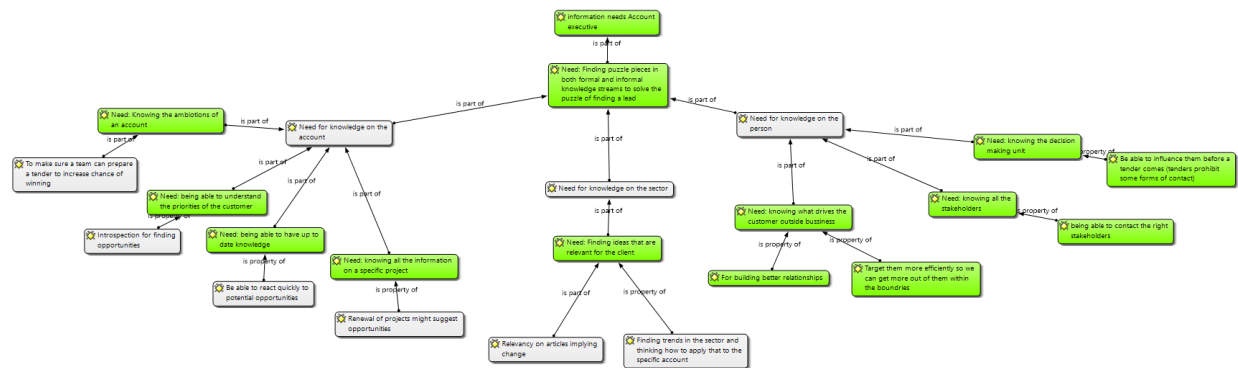


Figure 16 Concept map intelligence needs account executives

Knowledge streams for Account executives

In order to perform their function the account executive relies on several streams of information. These streams can be subdivided in 3 categories: information from the online sources, information from internal sources, and information from the customer network. First, several forms of information could be gathered from online sources. Interviewees mentioned presentations, the account' website, and formal plans as sources that could shed light on what direction a company is going. For a broader view on the whole sector, the account executives also mentioned being subscribed to newsletters of different companies, which gave broad knowledge over direction. Interviewees further mentioned using social media to know about the people they are dealing with, even though not a lot of information about deals could be extracted from these sources. As a last resort, they mentioned news on accounts. Anything going wrong was said to be relevant as a potential opportunity, however they noted that news is usually late. As mentioned by an account executive: *"if I read it for the first time in a newspaper, then I haven't done my job"* suggesting a good account executive should know what is happening within a firm before the news comes out.

Information from internal sources could be divided in 3 forms. First the account team gathered information. This information was shared with the entire team through account meetings. The individual team members decide what to share with the team. Next to the account team, the account executives also have a research team reporting to them. These teams produce reports on the specific accounts. The information is, however, not always recent and useful, it takes some time to produce the reports and the report might miss relevant information that is not deemed necessary by the research team. Finally, the account executive has teams focused on tenders. Via those teams, the account executive can get end dates (for deliverables) for projects running at the company. As stated by the account executives, this information is one-sided because it only focuses on dates instead of the complete picture.

The final information category comes from customer networks. These networks might give knowledge about future opportunities. By having informal communications, they can get to know a lot about the customer. These informal conversations come in several forms: workgroups, talks, meetings and bringing customers together for subject groups. These informal conversations were said to help streamline the intelligence that was found in the formal plans. The concept map of the intelligence streams can be seen in Figure 17.

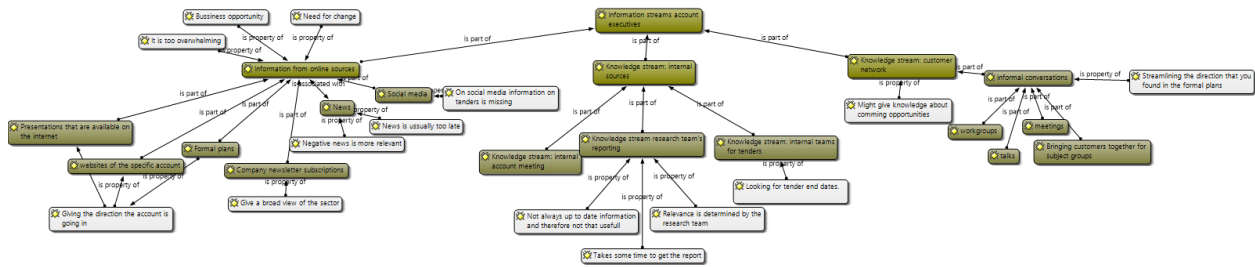


Figure 17 Concept map intelligence streams account executives

Intelligence gaps account executives

Figure 18 visualizes the match between the given demand for intelligence and the information system's supply. The information system does not supply information on the decision-making unit. Furthermore, the results of the interviews show that the need to know (be informed) about all the stakeholders, and what drives the person, seems to come from informal conversation only. An argument can be made that not all stakeholders might be known in this way. The interviewees mentioned that client members mostly connect with equally ranked members. Given that this information only comes from certain level of employees, a suggestion could be made that not all ranks are covered with this method of collecting information. The intelligence gap thus exists, in knowing the stakeholders within their target accounts including what drives (read: interests) them, their roles, how they are connected and the DMU.

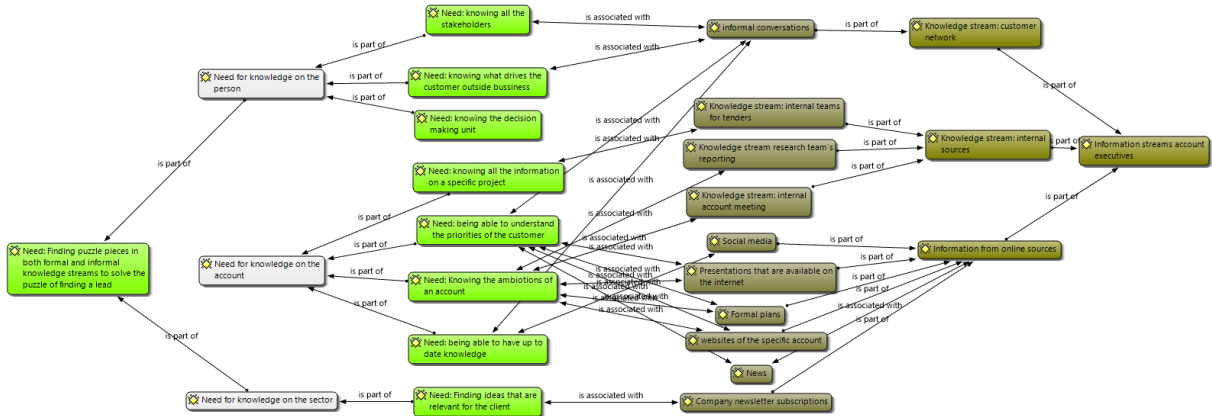


Figure 18 linkages intelligence needs and streams account executives

Presentation preferences for account executives

The account executives presented three preferences for how additional intelligence should be presented. First, they stated the need for it to be short and powerful. Second, they wanted information to be searchable through the intelligence database. Finally, the account executives wanted to be able to make changes to the system to their own preferences (and thus to be able to improve the system) (an overview of the codes is given in appendix C).

4.2 sources

An intelligence system should be fed with information from one or several sources. In order to determine what sources are available and how these look like, the codes were extracted from the interview transcripts about potential data sources, and combined with codes that explained about these sources. This was done for all transcripts. The codes were linked to form a map of potential sources.

Data sources

The data sources given by the employees during the interviews are represented in Figure 19 linkages codes data sources. For all data sources a description is given that summarizes the data source. From this summary, the codes indicating what information could be fetched from the source are displayed and the structure and extraction possibilities are looked up for these sources. A complete overview is given in Table 3 Data sources given in interview

Table 3 Data sources given in interview

Name	Description	Information	structure	Extraction
Analyst reports	Analyst firms are firms that report on the sector and the market and trends in marketing. The interviewees mentioned information that could be fetched on insights into the challenges coming. It is given that they report on a strategic field what is coming and what to focus on. Furthermore, analyst firms are said to report on positioning and branding of firms with their competitors.	Market trends Marketing trends Positioning/branding	Textual format: Unstructured	API call/ manual upload
Online published interviews and surveys	Online published interviews and surveys are defined as information from persons working at an account. These sources might contain information given by the employee on the direction and strategy of the account. One interview might not sum up all the information needed about the strategy, though it can help in providing a puzzle piece.	roles and interests of employees Strategy of account	Textual format: Unstructured. Surveys might come in semi structured format	Scraping from online source
Internal reports	Internal reports are reports made internally by research teams or other employees working on the account. Although much information is not given on these reports, it is stated that they could give information on the projects running at the account and their duration.	Projects running at accounts Duration	Textual format: Unstructured	Manual upload
Account website	The account website is given as a source of information and content. The site can give insights into the strategy of an account, provide their vision and might give insights in projects and project types.	Company strategy Company vision Insights in projects	Textual format: Unstructured	Scraping from online source
News	The news is said to give the challenges that the accounts are facing, what companies they are buying, when they are changing the strategy, potential opportunities and what development they are doing. There are some side marks given to news. News sources are said to be too late. The intelligence on the newspaper should be already known beforehand. The intelligence that comes from news sources should thus be filtered on relevance and on, relevant is dependent on how much it relates to the topics mentioned above. As mentioned one suggested correlation for relevance is	Challenges Buying habits Strategy Potential opportunities	Textual format: Unstructured	API call/scraping from online source

	the sentiment whereas negative news is said to imply the need for change more often and thus have more potential for relevance.			
Financial information and press releases	Financial reports (e.g. quarterly results) and press releases of an account could shed light on what the customer is planning to spend money, it shows their focus.	Customer plans	Textual format:	Scraping from online sources/manual upload
		Customer focus	Unstructured	
Blogs	Blogs give information directly about and from the person blogging. They contain information on how a person thinks and a direction this person is going. It might also contain information on the vision of companies	Information on peoples interests and direcrtions	Textual format:	Scraping from online sources
		Vision on company	Unstructured	
Forum	Forums can give information on the on post authors. In forums, people often give their opinion and state topics of interests.	Topic of interests	Textual format:	Scraping from online sources
		Opinions	Unstructured	
Social media	Social media and social networks are sources filled with user generated content. They could give information on the people working for an account and how they shift within the account. Social media could also shed light on personal/business interests and direction the person is going. Most mentioned social media source is linked in. Connections between people were said to be available.	Current role	Textual format:	API call/scraping from online sources
		Personal/business interest	Unstructured	
		Connections between people		

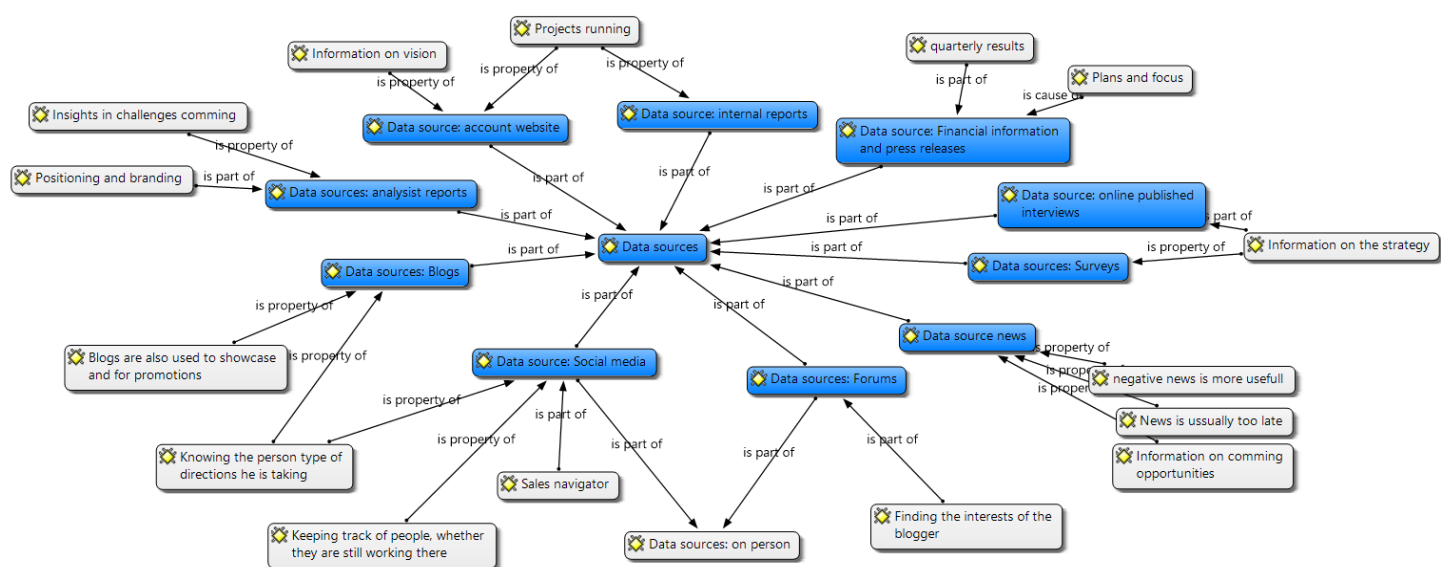


Figure 19 linkages codes data sources

4.3 Conclusion of the findings

What are the intelligence gaps that could be filled in with an intelligence system?

The findings give a good overview of the marketing information system, the intelligence demands and the intelligence gaps that might be filled in. The identified intelligence gaps differ depending on approach to marketing. The SBM managers identified wanting to know more on the people working at the customers (i.e. their hobbies roles and activities), how they are connected in a stakeholder map, and knowing the DMU. The Account executives were identified to need more information on stakeholders and what drives them and the DMU. Finally the PBM managers were identified to need more information knowing the customer's activities, interests whether they are part of a DMU and their contact details.

The recurring themes here are that all units of analysis were interested in the stakeholders and their interests/drives and the DMU of the customer. Both the account executives and SBM managers were also interested in the stakeholder's roles and how they are linked together. Both the PBM and SBM managers were interested in the activities of the stakeholders. An intelligence system could thus add by identifying the stakeholders in accounts, finding their interest, roles, activities, how they are linked together and whether they are part of a DMU. This intelligence needs to be as up to date as possible to be effective in the marketing efforts.

What data sources are available for an intelligence system?

Several potential data sources were given. Scoping the data sources towards the intelligence gap represented by knowing the stakeholders and knowing the stakeholder map suggest only several data sources to be useful. Social media can give insights into the role, interests and possible connections. Blogs can give information on interests and directions of people. Forums could help in finding topics of interests about and how people may think about those topics. Finally, online published interviews and surveys help in identifying roles and can show peoples thoughts on specific topics.

How would B2B marketers like the intelligence to be presented?

The presentation preferences also differed depending on the approach to B2B marketing. There were however recurring preferences. Both the PBM and SBM managers would like to have it implemented in their CRM system. Both the SBM and Account executives would like to have a search option and to have the intelligence stated brief. Furthermore the PBM stated the preference for an easy to use display, while the account executives mentioned they wanted the possibility to give edit preferences.

5. Discussion and conclusion

This research was concerned with exploring the possibilities of intelligence systems that could add to the marketing information system of B2B marketers. The previous chapter gave the results of the study. This chapter interprets the results and discusses the research. Section 5.1 starts with combining the literature on intelligence systems with the identified phenomena of the B2B marketing environment to answer the main question. Section 5.2 reflects upon the proposed outcome. Section 5.3 gives the strengths and limitations the research method. Section 5.4 discusses further research. Section 5.5 discusses the contributions to literature. Section 5.6 discusses the alignment of this thesis with the master program. The chapter will end with an overall conclusion.

5.1 Main findings

The previous chapters answered the sub questions. This section answers the main question:

How should an intelligence system look like to effectively add to the B2B marketing information system of an IT solution consulting company?

First the found phenomena of the B2B environment will be discussed on basis of the literature. The phenomena as discussed in the findings chapter will be reviewed using the literature on the B2B marketing environment to establish convergence and divergence with the literature. After the found phenomena are reviewed, they will be used to determine how an intelligence system for B2B marketing environment would look like. The framework for intelligence systems as described in the literature review will be used. For each layer within the framework, a choice will be made between the alternatives, based on the found phenomena. Finally, combining all choices of each layer for intelligence systems will provide an overview of how an intelligence system looks like for the B2B marketing environment. This overview is then reviewed on its ability to effectively add to the B2B marketing information system.

5.1.1 B2B environment

In this research phenomena on the intelligence needs and the marketing information system of the B2B marketing environment were found. These phenomena are reviewed based on the literature.

First, the intelligence needs are reviewed. As indicated by the requested intelligence needs, the marketers are almost solely focused on the customer in their professional activities. This theoretically contradicts the five forces as indicated by Porter (2004), since the marketers did not show interest in threat of new entry, supplier power, threat of substitution or competitive rivalry in the interviews. This does, however, enforce a clear distinction between B2B and B2C marketing. Consistent with this observation, Cortez & Johnston (2017) indicate that in B2B the focus is more on customer relationships than in the B2C environment. Likewise, Wouters (2004) argue that general information on the customer (e.g. processes of the customers, relevant stakeholders, trends and support) are more important to B2B. Gummesson (2004) suggests B2B marketers to be more interested in scoping down intelligence at a personal level, instead of knowing the customer as an aggregated mass of people in B2C. Easton and Araujo (2003) argue that specifically information that can be used to flag up potential problems and conflicts are useful to B2B marketers as opposed to B2C marketers.

Instead of having a wide information need, the respondents showed specific interest in intelligence on customer relationships. The requested intelligence was indeed scoped down, since overall intelligence on customers as a mass was not mentioned as an intelligence need, whereas information on the specific accounts (e.g. ambition and vision) and people (e.g. roles, interests and activities) were. Furthermore, the respondents mentioned to be specifically interested in events going wrong. As one respondent said: *“That's interesting; things going wrong, that's the thing we need”*. The information needs of for this case thus don't resemble overall marketing information needs; however do adhere to the specifics of B2B marketers.

The found intelligence gap for B2B marketers is information on a lower (read: more personal) abstraction level (i.e. roles, interests, activities, relationships and whether they are part of decision making units). This information is not uncommon in marketing literature since they are in line with psychographic

segmentation (Kotler & Keller, 2016; Nasiopoulos, Sakas, Vlachos, & Mavrogianni, 2015) since they can help in giving the marketers better understanding of their customers personality traits, lifestyle and values, to be able to better target them.

Second the B2B marketing information system is reviewed. The marketing information system should provide the marketers with the information they need. According to marketing textbooks, a common marketing information system consists of people, equipment and procedures to gather, sort, analyze, evaluate and distribute timely and accurate information to the marketers. The aspects on which such a system relies are internal company records (e.g. sales records, stock prices, cost and financial information), marketing research (i.e. specific information on demand) and marketing intelligence/decision support systems (i.e. a constant flow of information) (Kotler & Keller, 2016). The knowledge streams (e.g. sales representatives, news, engagement managers and analyst reports) found in this study do indeed suggest the availability of a wide marketing information system. So do the marketers obtain financial news and strategies (e.g. through news and websites and analyst reports), do they have access to on demand intelligence (e.g. marketing researchers and internal research groups), and are they kept up to date on trends and issues (e.g. sales representatives and engagement managers). In the case environment, IT based marketing intelligence systems, however, were not observed in the marketing information system.

As indicated by Arnott, Lizama, & Song (2017), IT based intelligence systems are mostly found in volatile and transitory environments, and therefore do not really occur in the B2B environment. This suggests that the unavailability of IT based intelligence systems as observed in the case of the marketing environment in our case company might be common. On the other hand, as indicated by Lilien (2016), this might be caused due to a lack of scientific research in this field instead of a lack of possibilities. Whatever the case, there is room for improvement.

5.1.2 Choices for intelligence systems

In an effort to answer how an intelligence system for B2B marketing will look like, the results of the case study are implemented in a proposed framework for intelligence system implementation as delivered in the literature review. The framework consists of several options for intelligence systems, most of which can only be applied when the environment suits the possibility. For each layer, below the options will be given, together with a proposed solution:

Sources

As also mentioned in the literature review, sources for intelligence systems can be distinguished between intelligence 1.0 (structured sources) and intelligence 2.0 (semi structured and unstructured sources) (Chen, Chiang, & Storey, 2012). The relevant sources given by the marketers were user-generated content (UGC) (i.e. social media, blogs and forums) and online published interviews and surveys. These sources are of an unstructured textual format, which implies the need natural language processing (NLP) and text mining methods. Due to all sources being unstructured and in textual format, a relevant intelligence system for B2B marketing can only be an intelligence 2.0 system.

New General Data protection Regulation (GDPR) puts more restrictions on the handling and collection of personal data. Data from secondary sources are not prohibited, given consent is in action from the person in question (Tankard, 2016). Most large platforms gather consent over the content they deliver. This consent commonly includes sharing via API. Per source, it might be needed to (double) check

whether the data could be collected by API calling since some sources might not give this opportunity. Scraping wouldn't be an alternative option to fetch the data from the source, since consent is commonly not given over scraping (Kerins, 2018) (See also appendix G).

Data extraction

Data extraction refers to the transformation of sources to storable and usable data. In the case of unstructured sources, the method describes what knowledge specifically is extracted. This is highly dependent on the intelligence needs of the practitioners (Sun & Wang, 2015). Due to all data sources being unstructured and in textual format, intelligence should be extracted using NLP and text mining methods (as also indicated above).

The sources are mentioned to contain information on people's interests, opinions, how they are connected and their current role. This resembles the intelligence that the marketers want to have. Extraction could therefore be suggested in the form of extracting data on relationships between: people and other people, people with roles, people with interests, people with activities.

NLP technology (as described in appendix E) suggests the possibility to extract this information. **Named entity recognition** recognizes of names in the text. This suggests the recognition of names or places together with the type this name belongs too (such as persons or locations). Methods for doing so are based on checking what words are capitalized or identification of names based on predetermined name lists. (Zhou & Su, 2002). This technique could help in recognizing people's names. Names can be cross checked with the CRM database and any form of text regarding the account they are working for should identify the person.

Relationship extraction is an application of NLP, in which the task is to detect and classify semantic relationships mentioned within textual data sets. An example of an approach is given by Ramakrishnan, Kochut, & Sheth (2006), who used a structure to tag parts of texts and relating known words with each other so as to extract relationships between the entities. Relationship extraction could be suggested as a next step to extract relationships of the entity (the person) with regard to interests, roles and other people (Voskarides, 2014).

Sentiment analysis describes the use of NLP to identify affective by extracting subjective information states (e.g. polarity like "positive", "negative" or "neutral", or emotional states such as "angry", "sad", and "happy"). The fundamental technology behind sentiment analysis is the classification (Pang & Lee, 2008). Sentiment analysis might give an indication on the state of a relationship -- i.e. whether it is positive or negative. A well-known example of a sentiment analysis tool is s Linguistic Inquiry and Word Count (LIWC) which uses a number of dictionaries to identify psychological phenomena (Crossley, Kyle, & McNamara, 2017). This form of NLP can help in identifying the affective state of the found relationships.

Theoretically extraction of the needed intelligence is possible. However more in depth research might be needed on the practical feasibility of automatic extraction of the needed intelligence.

Data storage

The method for data storage is dependent on what intelligence is needed. Specifically, issues to be considered are: the need for historical data entries, whether the intelligence need is multivariate and how many purposes the storage should serve. Several options exist, for data storage. Data warehouses could be used to store data. Data warehouses are massive repositories that can safe multivariate data

including historical entries (Bălăceanu, 2007). Operational databases provide a more suitable repository. These forms of storage are usually smaller due to this type of storage only storing current data entries and overwriting old entries. Historical data is therefore not recorded (Chaudhuri, Dayal, & Narasayya, 2011). Finally, data lakes are also an option. Data lakes contain data in their raw form, commonly without extraction (Botelho, 2018).

The found phenomena suggest the need for up to date multivariate data. Up to date intelligence and no need of historical entries, therefore there is no need for massive data warehouses. Options thus are: First, extracting the relationships and saving it in a database or, second, saving raw textual data in a data lake for further processing. Both methods for saving data are suitable for the B2B marketing application. Due to the raw structure, data lakes tend to take up more space, while in databases the data is already cleansed and categorized resulting in less storage (Botelho, 2018). Storage of meta-data in databases might therefore be more suitable than data lakes.

An effective intelligence system for B2B marketing can store data in a database. For the case company that was studied in this research, there was however a specific database option. The marketers also suggested the presentation preference for having the intelligence presented in their CRM system. The marketers use the Salesforce CRM system. The Salesforce CRM system runs on an Oracle database. The platform creates new tables for new tabs, customers, activities and leads (Salesforce Trailblazer, 2014). An intelligence system might add to this database.

A single repository might sometimes be used by multiple users who want different information. Data marts could help splitting the data for several purposes (Watson & Wixom, 2007). The found phenomena however don't suggest the need for splitting, and therefore no need for data marts.

Again, it should be stressed that storage of personal data is punishable under GDPR laws. However, when consent is given over the data, storage does not exceed the GDPR rules (Kerins, 2018). Furthermore, when legitimate interest is pursued, such as direct marketing and relationship building with clients, data storage and processing are legally allowed (Davis, 2017) (See also appendix G).

Data usage

After storage the data should be used. The intelligence need is the determining factor for deciding what to do with the extracted data. The found phenomena indicate a need for knowing relationships. This form of intelligence does not suggest analysis to be done on the data to find patterns. The descriptive form of intelligence diminishes the need for data mining.

There is a demand for multidimensional intelligence which can be examined on several viewpoints. Customers could be analyzed on their preferences for determining how to target, or sorted on values that show interconnection (for determining who to include in a campaign). Pivoting, slicing and dicing through data is therefore needed.

Chaudhuri, Dayal, & Narasayya (2011) describe the use of OLAP servers. OLAP servers are data using engines designed to support multidimensional data structures, and can help to expose a multidimensional view of the data. It makes it possible to filter, and aggregate through the data, slice and dice the data and pivot variables. OLAP servers can help in showing the multidimensional data from several angles (Bălăceanu, 2007). This will help in identifying needed information for the marketers. Furthermore, newer OLAP servers could be useful when intelligence is needed on larger datasets, which

cost significantly longer time to process. Pre-calculation in downtime can improve performance (Chaudhuri, Dayal, & Narasayya, 2011). An intelligence system for B2B marketing should therefore have OLAP servers implemented for data usage.

Intelligence presentation

After the data is used, the intelligence needs to be conveyed to the practitioners. The marketers stated three mutual preferences: having the intelligence stated brief, having a search option, and implementing it in their CRM system.

Bălăceanu (2007) describes fixed scheduled reporting, which refers to reports delivered on fixed moments. The marketers suggested the preference to search through the reporting for specific information. Fixed scheduled reports are better suited to convey general information instead of specific information. Therefore this method of intelligence presentation does not suit this goal.

Chaudhuri, Dayal, & Narasayya (2011) describe on demand reports. In the form of ad hoc query reports, practitioners can request reports when needed. Practitioners can also have the intelligence presented by scorecards or dashboards. Charts, colored metrics and tables can be used to give an overview of the dataset. This could be combined with the ability to view more detailed information (Ong, Siew, & Wong, 2011). More recently, relational graphs have been used for intelligence systems. Relational graphs give practitioners a quick overview of how elements are connected with each other and what the element environment might look like (Petermann, Junghanns, Müller, & Rahm, 2014).

Relational graphs might be the best way of presenting the intelligence. First the intelligence need is about knowing relationships which can be best depicted by using relational graphs (Petermann, Junghanns, Müller, & Rahm, 2014).). Furthermore, their preference of the intelligence being presented in short and brief form suggests that they don't have much time to read through large texts. A quick overview of the intelligence is thus needed. Relational graphs can provide this quick overview. Finally, this form of intelligence presentation could also be implemented in dashboards of other systems such as the marketers' CRM system. Relational graphs therefore suggest the best fit to establish the needed intelligence for a B2B intelligence system. Query searches can be applied as an input to filtering the data on specific relationships (for instance with an interest) or specific groups (for instance an account).Intelligence system

5.1.3 Intelligence system

This research tries to provide the answer to the question:

How should an intelligence system look like to effectively add to the B2B marketing information system of an IT solution consulting company?

Choices are made within each layer of the model which scoped down the model formed in the literature review according to the found phenomena. An intelligence system for that would effectively add to the B2B marketing information system of an IT solution company will be build out of the following components. First the intelligence system will use user-generated content (UGC) (i.e. social media, blogs and forums) and online published interviews and surveys as data source. Second, data will be extracted from these sources using NLP methods such as named entity recognition, relationship extraction and sentiment analysis. Third, the extracted data will be stored in databases. Fourth, OLAP servers will be used for slicing and dicing of the data. Finally the data will be presented as intelligence by use of

searchable relational graphs. This form of presentation could be implemented in dashboards of other systems such as the marketers' CRM system. When all components of each layer are combined with each other, a model for an intelligence system can be proposed as given in Figure 20.

The proposed model adds to the B2B marketing information system by providing intelligence that the current information system does not provide. In general, the B2B marketing information system provides marketers with several forms of knowledge on several topics (Eerden & Rodenberg, 2007; Kotler & Keller, 2016). In the researched case, the B2B marketing information system was found to focus towards customer intelligence, as that information is more needed for B2B marketers. The overall marketing information system does focus on customers. However, it does not give a complete picture. Knowing the customers can be done on several abstraction levels (e.g. on company level by knowing their vision and mission, on project level by development or choices and on personal level by knowing the people that work within the company). The identified B2B marketing information system does provide several knowledge streams on the higher abstraction level (e.g. analyst reports, annual reports, news, formal plans, websites). Unfortunately, it lacks on decent intelligence on lower levels of abstraction. These lower, more personal, levels are perceived as important tools for understanding the customer and pursuing efficient marketing.

The proposed intelligence system will be able to contribute intelligence that is currently not delivered by the marketing information system, but is demanded by the marketers. It adds to the information system by focusing specifically on the lower abstraction levels. As a consequence, it can provide a more complete picture of the customer.

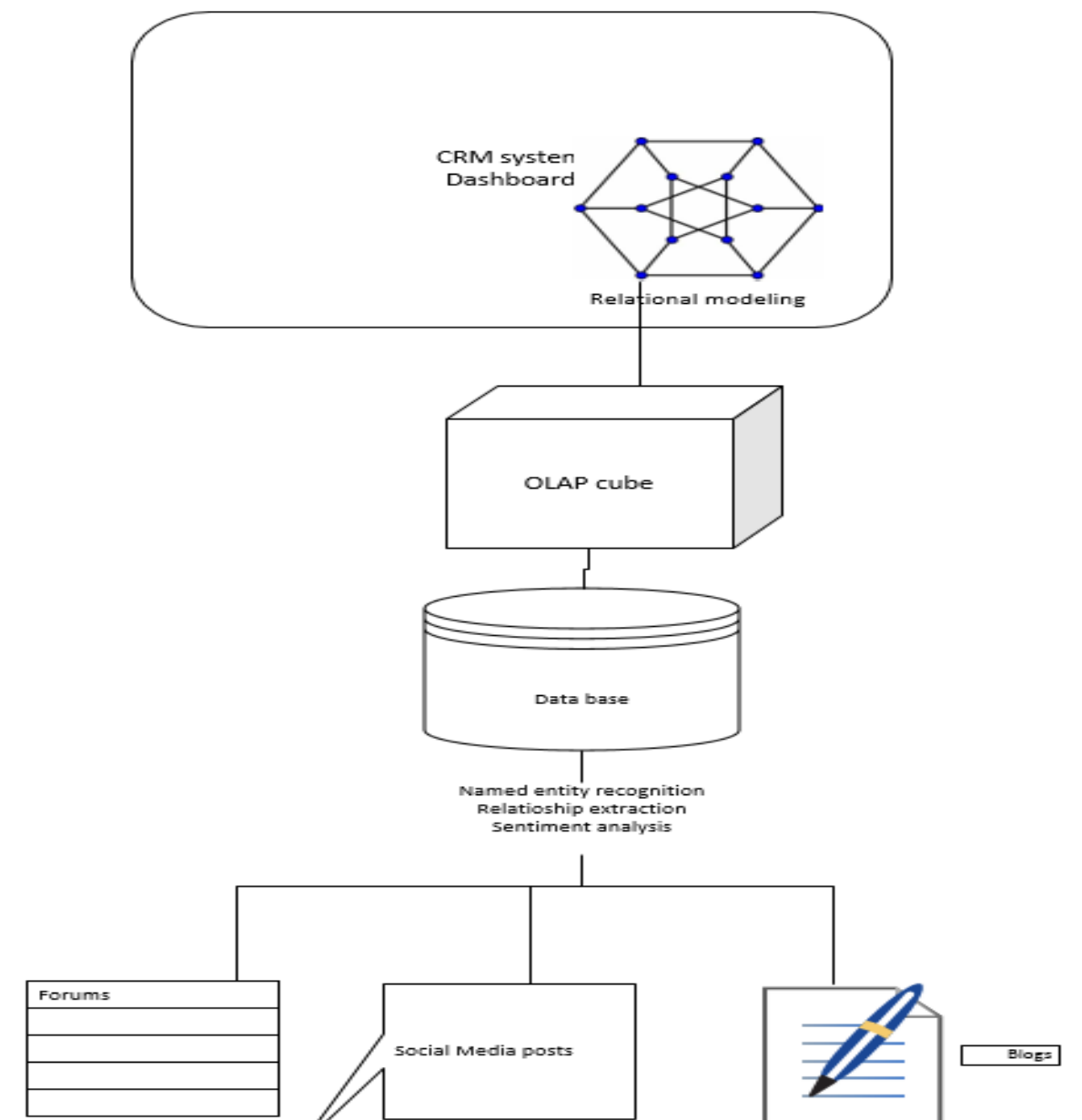


Figure 20 Overview intelligence system for B2B marketing

5.2 Reflection on the system

In this section, the proposed intelligence system will be reflected upon. First all layers of the proposed intelligence system are discussed. Second the intelligence system will be reflected on its effectiveness

5.2.1 Reflection on the choices

The research suggests that, theoretically, the use and implementation an intelligence system can be useful for B2B marketing. An intelligence system can be developed to extract additional information about people, and present it so that marketers targeting could be done more effectively.

Sources

This research opted to find out what types of data sources were available for intelligence system. The research did not take into account that sources could be produced and what the quality of the sources would be.

The described intelligence system is based on UGC. This type of data might lack in quality and completeness. Firstly, although the sources are openly available, this data might not be complete. The completeness of the data source is dependent on the activity of the person and the availability of information on that person. In other words, missing values in the intelligence system might be a problem (Fan & Gordon, 2014; Wu, Zhu, Wu, & Ding, 2013).

Secondly, quality of the data might be an issue. Watson and Wixom (2007) describe the notion “garbage in is garbage out” -- i.e. if poor quality sources are used, the intelligence will also be of poor quality. The validity and veracity of the sources is a determining factor. First, Sources that are not peer-reviewed and can therefore be biased and lack in validity. This form of text is referred to as “grey literature” (McAuley, 2000). Due to the fact that grey literature is used in the proposed intelligence system, the users should be aware of this validity problem, and how this might influence the quality of their intelligence, since it might not be correct or up to date (Gong, Cho, & Lee, 2018). Furthermore, because anyone can post anything, no regulation on truthfulness of the message exists. Finally, people don’t pay attention to spelling and grammar, which makes it even more difficult for a machine to process the natural text (Holecz, 2017). This might have consequences for any future Intelligence 2.0-based system, in which the functionality of text-mining should add value (see also Chen et al., 2012).

Extraction

A limitation to the proposed solution for data extraction is the practical ability of such an algorithm. Although the theory suggests the possibility to extract relationships from text, these algorithms might not be as sufficient as humans in identifying relationships due to the complexity of human texts. The quality of extraction is highly dependent on the algorithm used. (Hirschberg & Manning, 2015).

Because NLP algorithms might miss, or overlook relations from texts, additional manual research might be needed in some cases. As the intelligence system is part of a marketing information system in which also uses marketing research, intelligence for specific situations, e.g. 1 on 1 targeting for an request for proposal, should still be added by conducting on demand marketing research on specific topics (i.e. if specific targeted marketing is needed on a person the intelligence from the intelligence system may need to be added on by doing manual research).

Storage

Limitations to the proposed method of storage are the case dependent options and the regulation surrounding storage of personal data. First, as established, database storage without the need for logging seems to be the best fit for an intelligence system for B2B marketing. The meta-data extracted from the unstructured text should be saved. Although the method of saving was researched, it is case dependent whether saving options already exist. The case firm uses a CRM database which could possibly be used as storage for the meta-data. Storage might thus be case dependent.

Second, meta-data on relationships cohere to being personal data. The storage of personal data is prohibited under GDPR regulation unless it complies with several measures (i.e. if contractual obligation, a legitimate interest for storing and using data or that explicit consent has been given) (Kerins, 2018).

Data usage

Two limitations are found for the proposed data usage. First, the analysis of the interviews conducted with the marketers suggested that they were only interested in access to descriptive intelligence. They did not express any interest in more sophisticated applications, such as comparison, trends or other analysis, in the interviews. It is however biased to assume that the intelligence needs of marketers, therefore, as a rule should only be of descriptive nature. It might also have been the case that the interviewed sample of marketers might not have knowledge of the possibilities of data mining. Making them aware of the possibilities of data mining could spark some ideas as to how these techniques could collect useful intelligence for them. This would probably produce different 'wish-lists' in future interviews on the topic.

Furthermore, the proposed intelligence system uses OLAP servers to be able to slice and dice the intelligence according to specific needs of the marketers. Although theoretically it should be possible (Bălăceanu, 2007), real world technical feasibility of slicing and dicing intelligence of this form should still be proven.

Intelligence presentation

Limitations to the proposed method for intelligence presentation are the practical feasibility and the case dependent options. First, the proposed intelligence system presents the intelligence using a combination of relational graphs and querying inside the dashboard of a CRM system. Again, this should be possible. However, the practical feasibility of the combination of this form of intelligence with relational graphs and querying is not proven before.

Furthermore, the feasibility of adding to the in place CRM dashboard is case dependent. Other B2B marketing environments might have different systems in place that could be used for presenting intelligence. Therefore, for each case the feasibility should be checked.

5.2.2 Reflection on the intelligence system

The proposed intelligence system provides a new and innovative way of collecting useful intelligence. Not only does it provide a more complete view, it also provides a wide view of intelligence on a single location, making it easier for the marketers to find relations between intelligence.

Although it is theoretically possible, the question to whether it is truly needed must still be answered. Given the size of the case firm and the interaction the employees already have with the customers, the knowledge on the accounts and people might already be available. The knowledge might be embedded in the employees and is not being extracted (Festervand, Grove, & Reidenbach, 1988). This form of

knowledge is referred to as “tacit knowledge”, which resides within individuals and is hard to communicate and transfer (Newell, 2009). Frameworks and methods for transferring this form of knowledge do however exist (e.g. Festervand, Grove, & Reidenbach’s (1988) framework for transferring sales knowledge through managers or knowledge transfer through the use of CRM systems (Stefanou, Sarmaniotis, & Stafyla, 2003)).

In the interviews, the suggestion was made that the CRM system was not used to its full potential since it is not properly filled in. A good knowledge management system was also not observed to be in place. A suggestion could therefore be made for a barrier existing for employees to share their intelligence. More effective and complete intelligence might be gathered through that stream instead of the use of UGC based sources (e.g. a knowledge management framework in which hierarchical information sharing on customers is strongly supported). This suggests that further research should also be conducted to other methods of intelligence gathering than IT based intelligence systems since, by comparison, other methods might be more suitable.

There is however an advantage in favor of the proposed IT based intelligence system over a knowledge management system. Setting up a knowledge management framework might be hard (Zeng & Pathak, 2003) compared to setting up an intelligence system. Setting up a knowledge management system, especially in a large firm, is a radical change and costs a lot of effort. (Zeng & Pathak, 2003). Due to the proposed intelligence system being an addition to the B2B marketing information system, it can be integrated incrementally and does not need radical changes, making it less effortful to implement.

5.3 Strengths and limitations

In this research, several issues might have affected the validity of the outcomes. First, only one case firm was examined within a single business sector (consultancy). The group of respondents solely represented their own organization. It is unsure whether the same phenomena would be found in other consultancy organizations or companies in other business sectors due to the complexity of these firms. It is therefore not possible to guarantee the found phenomena to be applicable to all B2B marketers, to only service providing marketers or only to the case firm. An addition of more cases could resolve this weakness (Yin, 2014).

Nonetheless also strengths can be found in the method this study used. Using multiple approaches to B2B marketing as units of analysis and finding convergent answers in the approaches to B2B makes the case stronger. It suggests that the found phenomena are independent of the used B2B marketing approach.

This research strictly depended on qualitative data from one-on-one interviews. This form of data collection might have issued some communication issues. Firstly, language barriers might have had a negative effect on the outcomes. Neither the researcher’s nor the respondents’ native language is English. This may have led to different outcomes as the researcher cannot be certain whether the questions asked, were understood correctly (Squires, 2009). Secondly, it was impossible to determine whether the respondents replied honestly. The respondents might, for example, have responded with personal desirable information needs, or withheld some information streams because of personal reasons. This could have negatively affected the results (Sekaran & Bougie, 2010; Baxter & Eyles, 1997). The internship however, made it possible to have more in-depth knowledge about the on goings of marketers which resulted in better understanding during the interviews. Furthermore, the marketers were not restricted in sharing their point and were not influenced to give specific answers which make

convergence between respondents more valuable. The freedom given to the respondents ensure more honesty since the participants can withdraw from giving information (Shenton, 2004). Finally, the inclusion of a second coder reduced objectivity and increased the reliability of the methodology (Hutchison & Skodol-Wilson, 1992).

5.4 Future research

Future work can be divided in rigor adding further research towards the found B2B marketing phenomena, additional research for intelligence systems implementation and additional research to other forms of intelligence systems.

This research examined the B2B marketing environment including their preferences regarding intelligence, intelligence needs, and marketing information system. Although multiple B2B marketing backgrounds have been examined, it is still not possible to prove whether the phenomena of the case study actually represent the B2B services environment. Due to the in depth methodology used for this research on a specific case firm, future research should look for cases to extend the external validity e.g. by looking at other B2B service cases or comparing with product driven B2B cases (Yin, 2014). Furthermore, the found phenomena (although from multiple respondents) come from one method of research, being qualitative interviews. To ensure the phenomena are not dependent on the method of research, different research methods should be executed e.g. the phenomena could be researched by introspection (i.e. self-identification of the phenomena by for instance working as a marketer) or observation (i.e. observing the workings of the marketers to derive the phenomena) (Goguen & Linde, 1993). It would be possible that future cases within the same sector or across industries would in future work lead to more possibilities for developing an intelligence system, e.g. due to different or more complete internal databases

In this research an intelligence system set up is proposed. This research provides a clear overview on what such an intelligence system would look like, however a deep dive in each of the layers on feasibility might still be needed. First, the sources should be further researched on their availability, validity, relevance and GDPR compliance. Second, the method for extracting relationships out of textual data sources should be tested. Third, places for storing data should be further sought; in place systems should be examined including possibilities in already available databases, and GDPR compliance of these methods for storage. Fourth, the implementation of OLAP system for data usage should be examined on relevance and feasibility to determine whether it is possible and whether it suits the goals of the B2B marketers. Finally the possibilities of relational graphs should be examined and the possibilities of integrating intelligence presentation in other systems' dashboard should be checked on feasibility. Answering these questions will give the knowledge needed for implementation of an intelligence system for the B2B marketing environment.

Furthermore, additional research should be conducted towards other methods for receiving intelligence for comparative purposes. Examples are: knowledge management frameworks (Festervand, Grove, & Reidenbach, 1988) and barriers for knowledge sharing trough CRM systems (Stefanou, Sarmaniotis, & Stafyla, 2003). This might further prove the effectiveness of an IT based intelligence system, or find easier or better alternatives for gathering intelligence.

5.5 Research Contributions

This research has made contributions in several ways. The practical contribution comes forward in the form of the intelligence system design that can be applied for B2B marketing purposes. This research however also made scientific contribution. First contribution of this research comes from filling in the knowledge gap for intelligence system implementation. The framework for intelligence system implementation as shown in the literature review combines knowledge from multiple researches and research domains. The 5 layer design of the framework is an adaption from Ong, Siew, & & Wong (2011) and Chaudhuri, Dayal, & Narasayya (2011). The framework combines research to define possible options for intelligence system within each layer. Finally the framework adds challenges for implementation for the options to steer implementation possibilities for intelligence systems depending on the implementation environment.

A framework for intelligence system such as Ong, Siew, & & Wong's (2011) and Dayal, & Narasayya (2011) are described with the purpose of assessing already established intelligence systems (or intelligence system plans). The objective of this research was however to explore how an addition could be made to the marketing information system using intelligence system. Therefore the already established frameworks were not specifically usable. The proposed novel framework in this research adapts several researches to fulfill a prescriptive purpose in checking whether intelligence systems could be implemented. The layout might look similar as the frameworks of Ong, Siew, & & Wong's and Dayal, & Narasayya. However an addition of requirement of the environment in the form of challenges for implementation makes that this novel framework can fulfill this different purpose.

This novel approach to intelligence system implementation helped with finding a solution for the B2B marketing environment. The approach could be used for more cases, even outside the marketing domain, to determine the possibilities of applying intelligence systems. Although it was not rigorously compared to other approaches, it might certainly be useful in similar researches.

The second contribution comes from identifying specific phenomena of the B2B service marketing environment. Research has been done to information themes marketers are interested in (Porter, 2004), and research is done towards how the B2B environment might be different to the B2C environment (Cortez & Johnston, 2017; Wouters, 2004; Easton & Araujo, 2003; Gummesson, 2004). However, clear identification of the phenomena within a B2B service marketing environment were not identified. This research addresses this literature gap by identifying the phenomena of information needs of B2B, B2B marketing information system and their preferences for IT based intelligence systems. First, the information needs of B2B marketers can be used as groundwork for multiple purposes. It could be used as groundwork for designing systems for B2B marketers. These systems don't have to be restricted to IT-based systems. Other kinds of systems could also be designed like knowledge management systems. The identification of information needs can be useful for identifying whether information system used in other environments might also be useful for the B2B marketing environment.

Furthermore, this research contributed by mapping the marketing information system of B2B marketers. Although literature exists on marketing information systems (Negash, 2004; Kotler & Keller, 2016), these mostly talk about the different facets within the marketing information system and are discussing the system for marketing overall. Marketing information systems for B2B marketing are not discussed and the information streams that fall within the facets are not specifically mentioned. This research provides

an overview of what information a B2B marketing information system might provide, thereby filling a literature gap.

Next to identification of information gaps, the results of this case's B2B marketing information system could be used for comparative purposes to determine how B2B service marketing information systems are different from other information systems.

Finally this research adds literature on intelligence presentation preferences. No previous work has been found on the preferences for intelligence presentation of marketers, let alone B2B marketers. This information might be useful as input for designing systems for B2B marketers.

It should be mentioned that the identified phenomena are from a single case research. However for comparison and giving direction to future work these findings can certainly be useful.

5.6 MOT curriculum alignment

The curriculum for the Management of technology master tries to improve the quality of technology and innovation management. The program provides the tools to be able to explore how technology can be used to advance the processes within businesses. Exploration, knowledge management and innovation are core themes of the program (TUDelft). This thesis aligned with the goals of the program. By analyzing the possibilities of intelligence system within the B2B marketing environment, this thesis adheres to exploring innovative and new methods to improve a process within a business. The study touches upon different topics of the program. As examples, the analysis of the marketing environment was based on previous knowledge from the high tech marketing course, the methods used was inspired by research methods books, and the distinction and understanding on knowledge management activities was based on the teachings in Leadership and Technology Management. This research therefore leveraged both the knowledge and objectives of the management of technology program.

5.7 Conclusion

There is a clear and need to exploit available data and technologies to produce new business systems toward more data-driven decision making. Information providing systems, including intelligence systems, are specifically suited for these tasks, as they provide the possibility for extended knowledge delivery and discovery.

Despite the high potential of these systems, research in the field of possibilities for B2B marketing has not delivered, and is lagging behind. The integration of intelligence systems within the B2B marketing environment was therefore explored in this research, with the aim of providing recommendations for future implementation. Exploration of possible methods for implementation, and results of interviews with marketers in the industry, led to the conclusion that B2B marketers focus primarily on the buyer-seller relationship. As a consequence, the B2B marketing information system does provide information on customers, however does so on a high (read: general) abstraction level. The B2B marketers indicated a need for information on a lower (read: more personal and precise) abstraction level. This kind of information is currently not provided by the marketing information system. An intelligence system based on the tools and techniques offered by electronic and mobile commerce could provide such intelligence on the customers, specifically regarding more personal intelligence streams.

Specifically, with web-based UGC as a source, intelligence on relationships, interests, roles and activities could be extracted. This would improve the possibilities for marketers to position, segment, and market their accounts. The type of intelligence system that is recommended for future implementation would extract information from these unstructured sources with the use of natural language processing to provide marketers with detailed and personal information that their current information system does not provide (i.e. information on the personal level of their customers).

By integrating the proposed intelligence systems, the B2B marketers will be able to target their marketing efforts better towards their customers and thereby might increase the effectiveness and obtaining more orders. In doing so, they can keep up with their

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Appendices

A. Topic list interview Marketing and sales	79
B. Inter-coder reliability.....	80
C. Networks of codes and diagrams	82
D. Machine learning.....	88
Supervised learning	88
Unsupervised learning.....	90
Neural Networks.....	90
Reinforcement learning.....	91
E. Natural language processing	93
Text mining and analysis	93
Application of NLP	94
F. B2B marketing structure and marketing activities of the case firm.....	97
Marketing structure	97
Marketing activities.....	98
G. GDPR.....	100
H. Sumerized literature table for intelligence system implementation	101

A. Topic list interview Marketing and sales

This appendix is referring to the topics proposed for the interviews. These topics were established toward getting most information as possible out of the interviews. The topics were determined based on the conceptual framework posed after the literature review, and the knowledge gathered from preliminary knowledge gathering. The interviews were held as semi-structured to establish the possibility for the researcher to get additional information on a topic if needed. Therefore, this topic list is used as a guide for the researcher and is not to be followed specifically.

- What department do you work for?
- What is your function in this organisation?
- What does your function entail?

- Do you in your Profession need information or intelligence?
 - What kind of information do you need?
 - Why do you think this information is necessary for your profession?
 - Do you use the found information in your profession?
 - What source does that information come from
- What systems do you have to deliver you information?
 - What information is this system giving?
 - What are strengths and limitations to those information streams?
 - What are the limitations of these systems and methods?
- Is there information that is not given by systems but should be available through sources?
 - Also information that is too high in quantity structure?
 - What data sources are useful but not used due to their quantity or structure?
 - Are there other (structured and non-structured) sources that information could be gathered from?
- If a system would be in place that would give you additional information, how would you like this to be presented?

B. Inter-coder reliability

Inter-coder reliability was applied to measure the amount of overlap between the researcher and a second coder independently. Both coders coded the same transcript which was randomly chosen out of all transcripts. The coding categories were given to the second coder and highlighted in the table below. These were: the intelligence needs and why, the available knowledge streams and why, the potential data sources for an information system and the nonfunctional requirements stated by the interviewee.

The first column below gives the codes as found by the researcher. The second column states the codes found by the second researcher. Because of terminology, the determination whether 2 codes were referring to the same was decided based on the highlighted text and mutual agreement between the researcher and second coder. Overlapping codes were given a score of 1 while non-mutual codes of both parties were taken in to the total but were given a score of 0. This led to a total of 72.22% overlap and thus a coefficient of 0.722.

Table 4 Inter-coder reliability coefficient

Researcher	Second coder	
Information needs	Information needs	
Challenges they are facing	Translate challenges out of sources	1
Need to know the person	Know the customer	1
need to know what day to day issues he is looking at	What are their key issues	1
Why	Why	
Message personalization	message personalization	1
Get to 1 on 1 marketing		0
Target them more efficiently within the boundaries	target more efficiently	1
	applying the right technique	0
	marketing automation	0
Information system	Information system	
sales people	Business leads	1
analyst reports	analyst reports	1
researcher	our researcher	1

Why	Why	
Indirect	Not directly coming from horses mouth	1
Averaged out	Averaged out view	1
Data sources	Data sources	
Social media behavior	Facebook/Instagram	1
Online activity		0
Blogs	Forums	1
Presentation	Presentation	
Can't be a different tooling		0
Integrated in the CRM system	Integrated in the CRM system	1
	Sum	13
	Total	18
	Inter-coder coefficient	72,22222

C. Networks of codes and diagrams

The figures following describing the linkages between coding were extracted from Atlas.ti and represented below. Each interviewee family was divided, and each group was represented dividing the codes in to 16 network views.

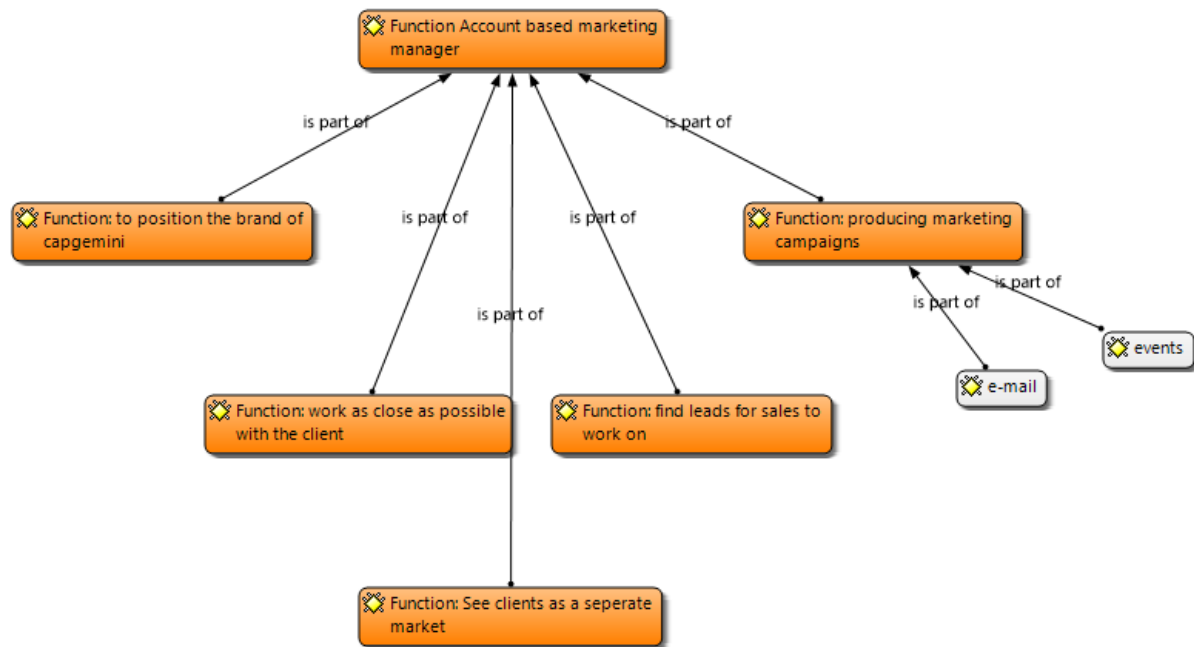


Figure 21 Function ABM

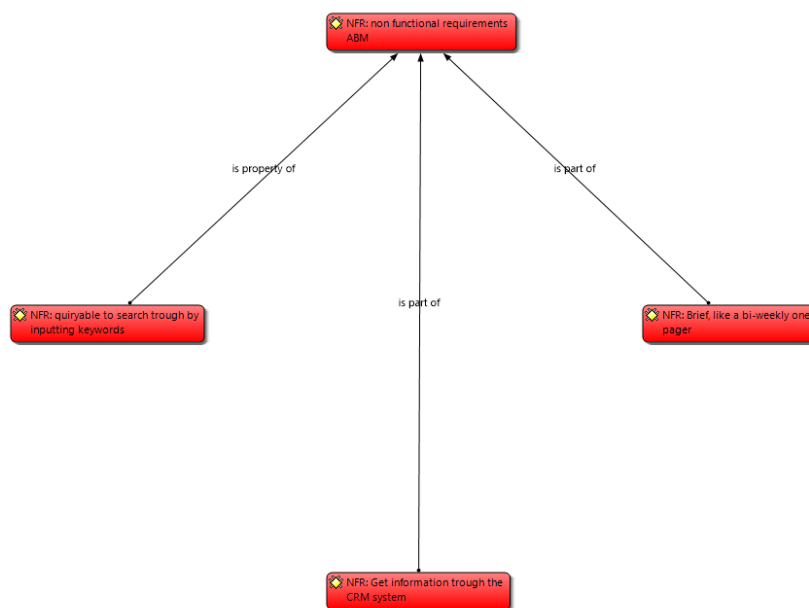
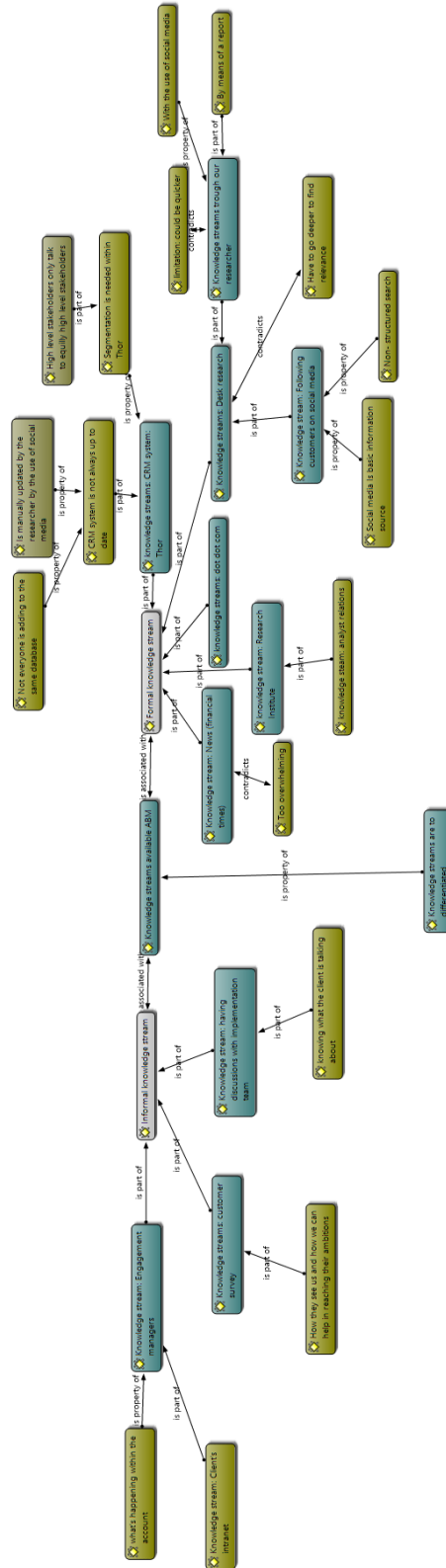
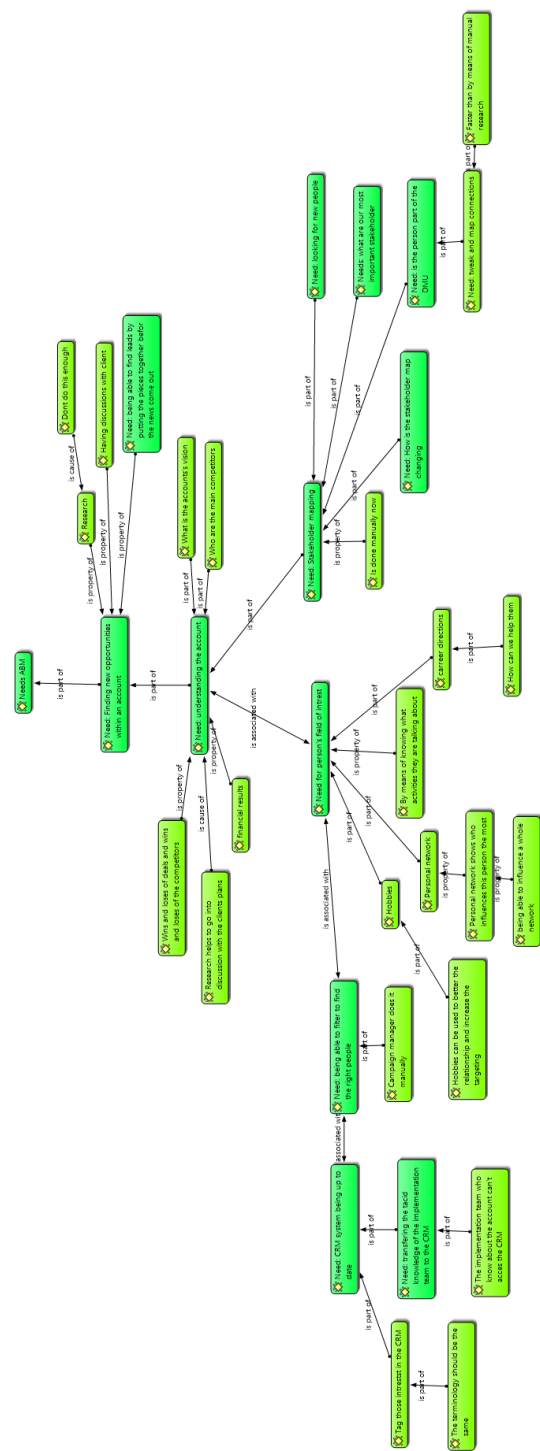


Figure 22 Presentation preferences sector based marketers



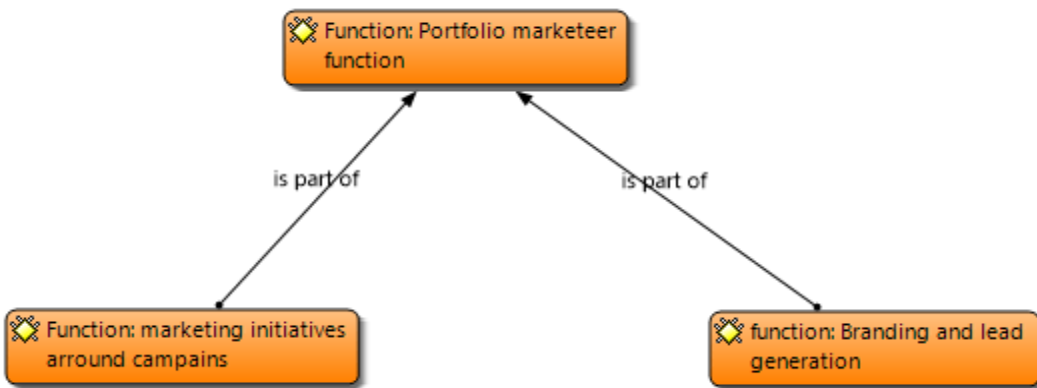


Figure 25 Function portfolio marketers

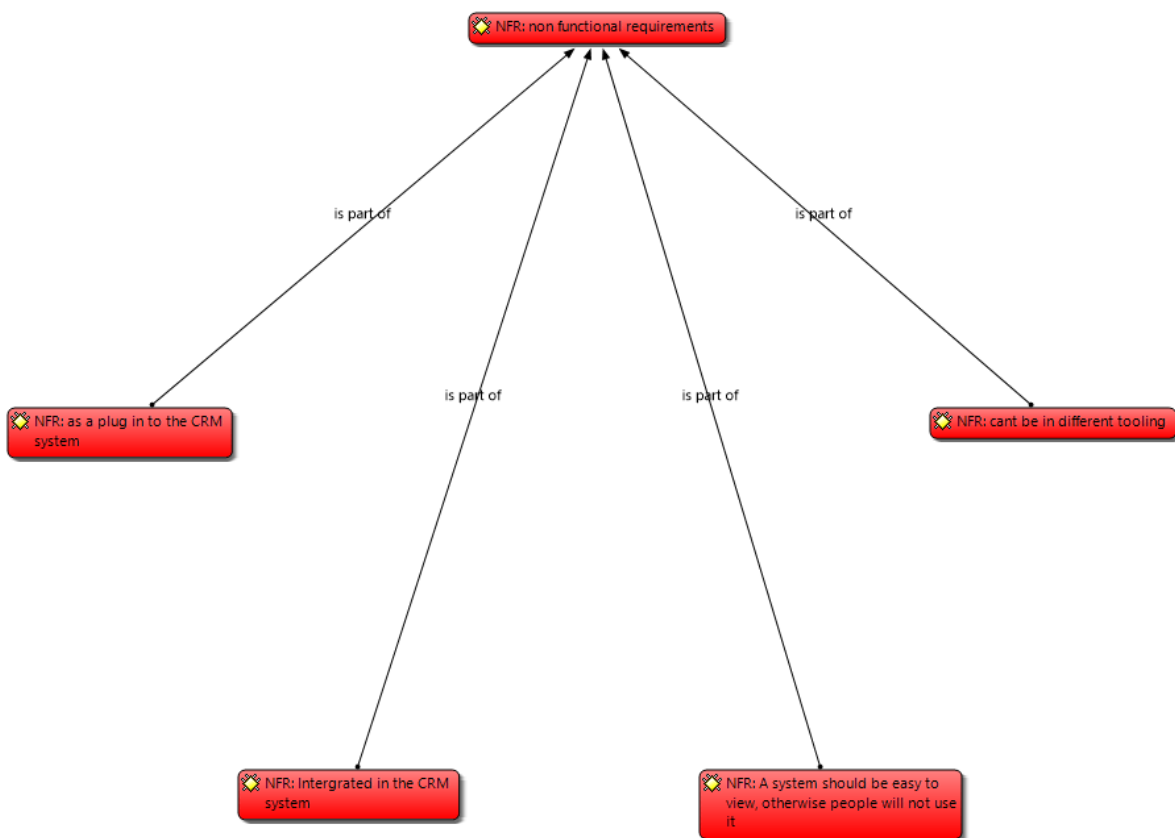


Figure 26 Presentation preferences portfolio based marketers

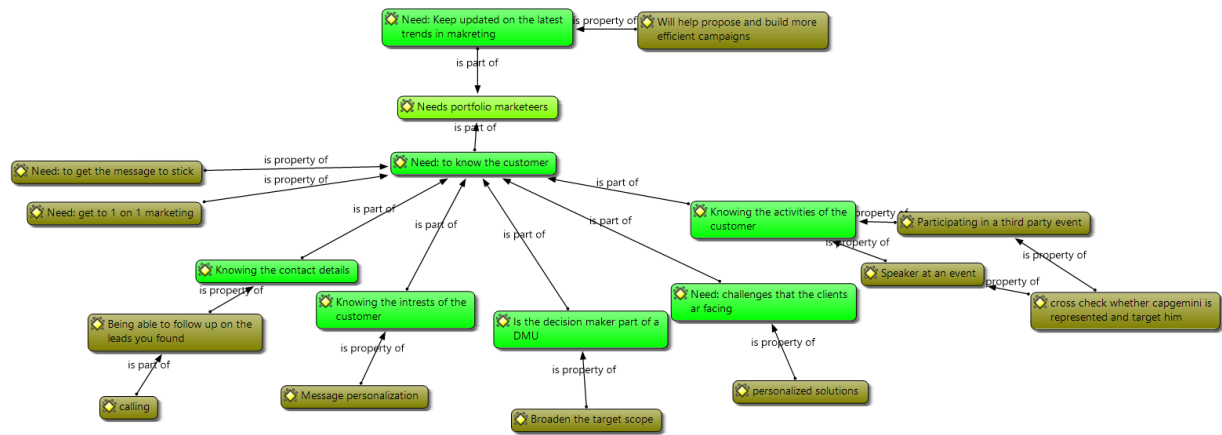


Figure 27 Information needs portfolio based marketers

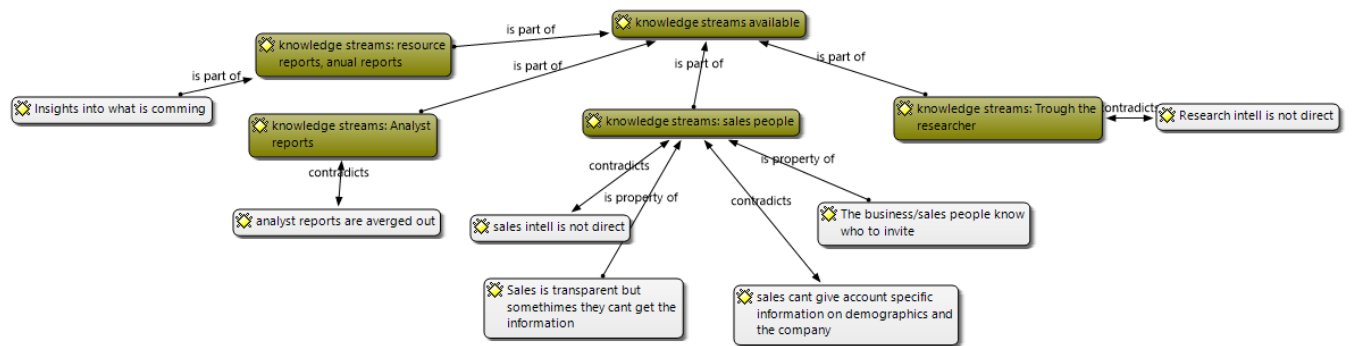


Figure 28 Information streams portfolio based marketers

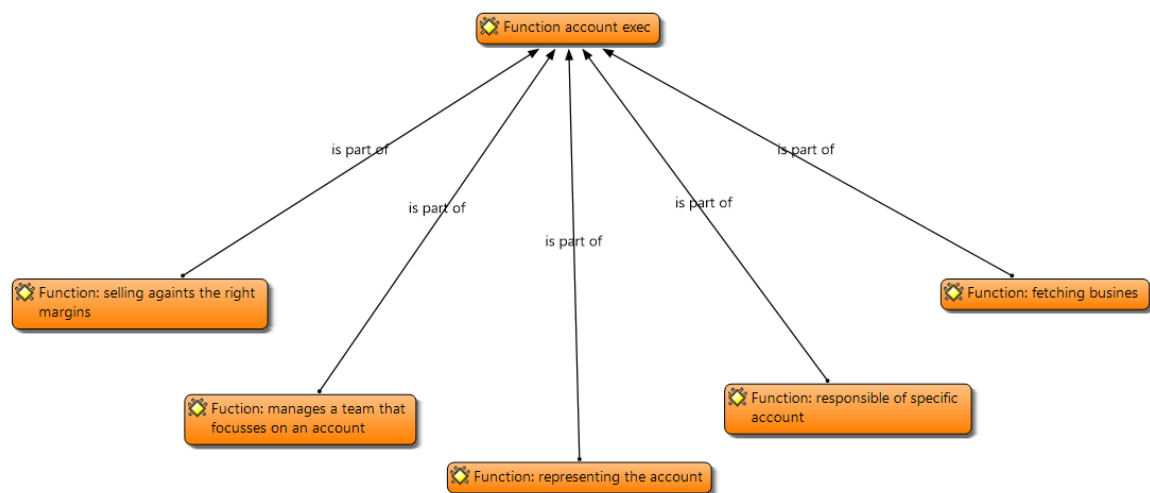


Figure 29 Function account executives

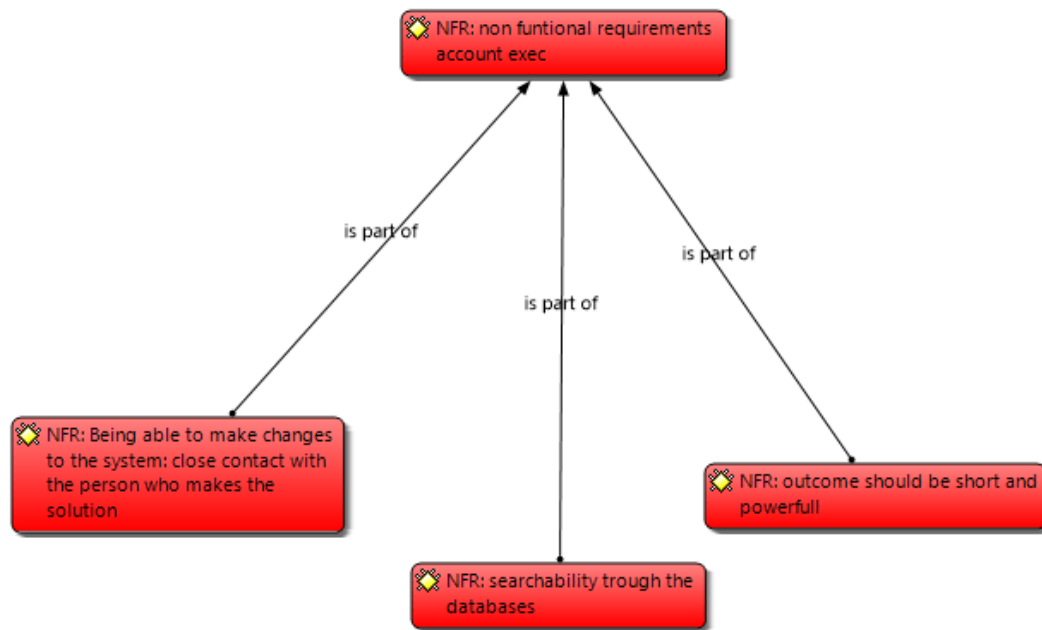
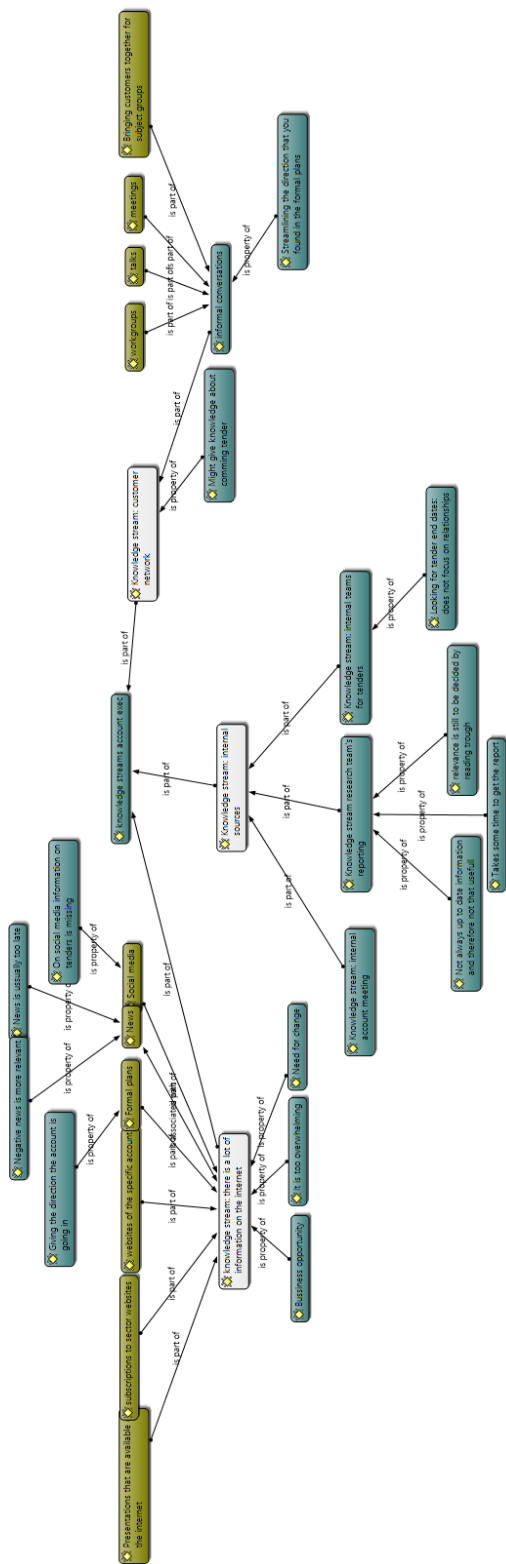
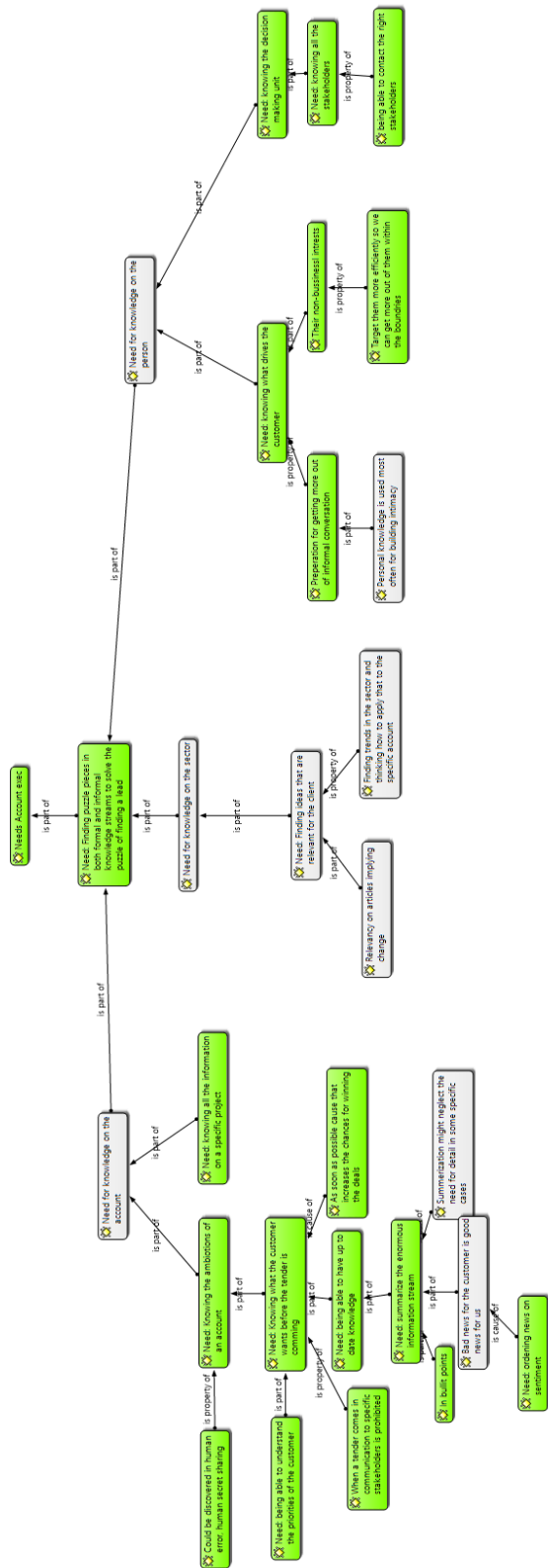


Figure 30 Presentation preferences account executives



D. Machine learning

This appendix will go into the various categories of machine learning. A basic understanding of the different machine learning algorithms can give a good understanding on the possibilities that machine learning can accomplish in solving the problem at hand. I will go forth on the list given above about the possible machine learning algorithms and will try to find out which of these algorithms suits best in accomplishing data analysis of such systems. The categories of machine learning are: Supervised learning, unsupervised learning, reinforcement learning and deep learning.

Supervised learning

Supervised learning refers to a learning that matches an input to an output on the basis of examples input and output pairs. The given input-output pairs are referred to as training data. The main purpose is to continue mapping input and output pairs by learning from the training data. This kind of algorithms can help labeling unlabeled data. (Russell & Norvig, 2009). Difference can be made between training data that is continuous against a finite set of training data. The latter is handled with a classification approach while the continuous training data is handled with a regression approach. Regression analysis is for instance used in weather forecasting in which past weather patterns are used together with the current weather elements to predict the coming weather. There are several supervised algorithms available. Before choosing a supervised algorithm, several issues must be considered.

By using supervised algorithms patterns are sought in labeled data. This could eventually lead to finding patterns in the training data that do not come forth in the population data. This means that the algorithm is specifically tuned to the training data and is therefore not applicable for other data sets anymore. Dietterich (1995) calls this symptom overfitting. Protection against this system could be done by testing the data. The accuracy of the input output pairs should be evaluated. Briscoe and Feldman (2010) describe this to be between bias and variance. They describe it to be as sliding a scale that modulates how closely any learning procedure adheres to its training. At one hand, high complexity can be accomplished by having highly variance training data with the risk of overfitting. Having a system that can make relatively simple and inflexible assumptions due to a less variant training data set has the possibility of underfitting.

Another aspect to keep in mind is the complexity of the underlying true function. If the function is not complex, high biased training data might be able to solve it, however when the true function is complex than a high amount of data might be needed to learn it a good overview can be seen in Figure 33 The need is than for an algorithm with low bias and high variance. (Russell & Norvig, 2009)

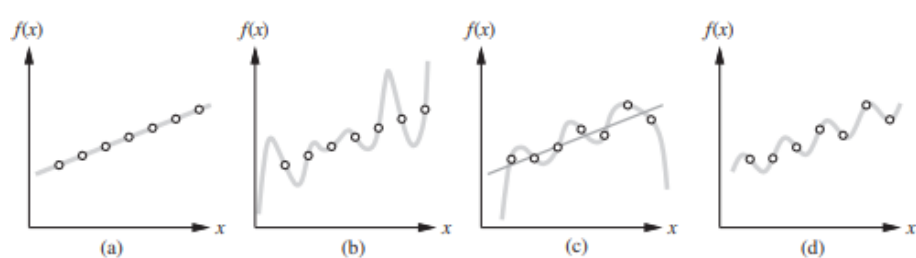


Figure 33 Correlation between complexity and available training data (Russell & Norvig, 2009)

Another possible aspect is the dimensionality of the input data. If the input data has multiple dimensions, while not all dimensions are needed to come to the right output, the extra dimensions in

input data could confuse the learning algorithm. This would lead to high variance in output data while low variance is needed. An option to solve is to mutually remove irrelevant dimensions from the input data, or to use algorithms for dimension reduction such as described by Fukumizu, Bach, & Jordan (2004).

The last aspect that must be considered is noise. When training data is given in the form of input and output pairs, some outputs could be incorrect. Incorrect output will lead to the function not being able to reproduce the true function. The errors could be focused on a on part of the function resulting in that part to be learned wrong or could be spread in the complete model (resulting in the whole function to be wrong). To solve such a problem, Brodley and Friedl (1999) suggest creating algorithms that would function in noise filters for the training data.

There are several algorithms available for supervised learning. The most common algorithms are:

- Support Vector Machines: A two group classification algorithms. It assumes input vectors to be non-linearly mapped with high dimensions. This causes high generalization abilities (Cortes & Vapnik, 1995)
- linear regression: This algorithm uses predictor functions whose unknown datapoints are estimated from the given data. More data increases the possibility of the linear regression to be correct, however complex non-linear functions are not supported. (SEAL, 1967)
- logistic regression: same as linear regression it algorithm uses predictor functions whose unknown datapoints are estimated from the given data. However, this model can interpret more complex logistical functions.
- naive Bayes: This algorithm assigns class labels based on the input data's dimensions. This algorithm however assumes all features to be independent without being able to generate correlations. This would reduce the chance of overfitting, but also isn't able to solve complex questions (Russell & Norvig, 2009)
- linear discriminant analysis: A pattern recognition algorithm that uses separation of classes to solve problems. It uses probability density fiction to determine the probability of the second variable is part of a given class.
- decision trees: an algorithm that predict the value of the target carriable based on previously given input variables. By using several dimensions, it can classify unlabeled data by using the labeled data to set up several yes or no questions based on the learning data due to this, this algorithm are susceptible to noise. (QUINLAN, 1985)

Unsupervised learning

Where supervised learning is trained by using labeled data, unsupervised learning handles unlabeled data. Because the data is unlabeled, finding the labels is one of the major components. Being able to understand the data and find the meaning of the data is key to this variant of machine learning. In huge amounts of data, patterns are sought in observations and variables instead of labels.

Classification of the data can thus still be established due to knowledge over the variables. A structure can then be formed within the datasets depending on several variables. The developer of the algorithms does not know how these variables are classified and how these groups are formed. The data is enriched with labels. These labels are not given, so the user does not know the variables. The data could then be clustered to give groups of data that have similarities (Hurwitz & Kirsch, 2018).

As described by Russell & Norvig (2009), unsupervised learning is most commonly used in clustering: detecting potentially useful clusters of input examples. But this is not the only potentially useful aspect. Unsupervised learning, by tagging, will have the ability to have a rich understanding of the data. This proposes the possibilities of tasks such as summarization and question answering (Chambers & Jurafsky, 2008).

Finding variable and relationships in data can be done with different algorithms and approaches.

- K-Means: partitioning data sets into k groups. This will be proceeded by selecting k cluster centers iteratively refining them by assigning the data point to the closest cluster, followed by an update of the data center (Wagstaf, Cardie, Rogers, & Schroedl, 2001)
- Density-Based Spatial Clustering of Applications with Noise (DBSCAN): is an algorithm that clusters groups together. Tagging them to a group. The main difference to the K-Means algorithm is that this algorithm removes outliers (N.Tran, Drab, & Daszykowski, 2013).

Neural Networks

An approach to tagging and enriching data is neural networks. Neural networks are networks build to resemble the human brain. It approaches problems by implementing layers of interconnected units to learn and find relationships in data. Such a network can have several connected layers. The layers in between the first and last layer are usually referred to as hidden layers. A network with more than one hidden layer can sometimes be referred to as deep learning (Hurwitz & Kirsch, 2018). Neural networks are combinations between nodes that are sometimes referred to as neurons. These connections are made with links that are sometimes referred to as synapses. These links have variable weights or edges. These edges can change to according to the learned material. By doing so, signals pass through differently. In large neural networks, the first layer is referred to as the input layer where the signals come in, and the last layer is referred to as the output layer where the signal comes out. The more layers in between suggest the ability to solve more complex and nonlinear problems. Output can (for supervised learning) be compared with a threshold to check whether the output matches the expectation. If not adjustment in edges will be made to stabilize the network. Such networks could thus be trained to enrich data if trained for recognizing variables. Because programmers do not know the steps between the input and the output, neural nets could be a Blackbox. It could therefore use decision variables that are not known and therefore be able to make better decisions. This gives neural nets the

potential to predict future events. Odom & Sharda (1990) , for example, showed the possibility to predict bankruptcy.

Reinforcement learning

Reinforcement learning is another part of machine learning. This technology is described as a behavioral learning model. The algorithms used for reinforcement learning thrive on feedback given by the analysis of the data. The main difference between reinforcement algorithms compared to supervised learning algorithms is that reinforcement algorithms don't learn with sample data. Instead it learns from trial and error. A sequence of found errors in from the algorithm will result in the algorithm being reinforced (Hurwitz & Kirsch, 2018). In a standard reinforcement model, the algorithm relates to the environment via perception or action. If the algorithm interacts with the environment it receives feedback as an input. This feedback is combined with the current state of the environment and translated in a suitable action. Changes in the environment are given as an input to the algorithm so called "scalar reinforcement signaling" (Kaelbling, Littman, & Moore, 1996). A depiction of this process is given in Figure 34.

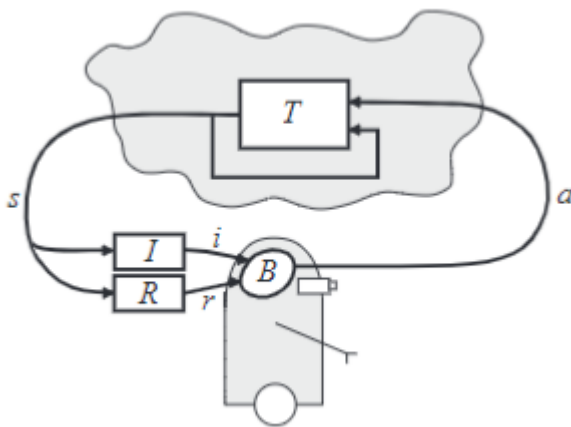


Figure 34 Reinforcement learning (Kaelbling, Littman, & Moore, 1996)

Three models are described. The Finite-horizon model, the average-reward model and the biased optimal model. In the finite-horizon model the in which the algorithm is asked to optimize its expected reward for the next predetermined number of steps. This model takes the long-run expected outcomes in to account, however these long terms expected outcome are discounted. This model is however not appropriate if the life length of the algorithm is not known. With average reward model the algorithms are expected to optimize the long run average reward. The algorithm is therefore searching for the optimal policy to be implemented. A downside to this model might be that there is not distinguishing made between policies that get a lot of reward in the beginning, or rewards that are averaged out in the long run. Therefore, this model might be insufficient for finding a maximum reward in the long run. In the bias optimal model this problem is tackled. The algorithms are asked to provide a policy that maximizes the long run average. Ties between policies are than broken by the extra reward.

Approaches

Reasoning is described as completing incomplete data. Hurwitz & Kirsch (2018) describe machine reasoning as helping to make sense of connected data and giving a system the ability to derive use the context to derive the answer using a logic chain that connects data to be able to better interpret the data by filling in the knowledge gaps. Bottou (2014) describes it as “algebraically manipulating previous acquired knowledge to answer a new question”. He also describes that for a system to be able to reason, it should first learn from an appropriate labelled training set. A solution to making a system able to reason is to feed it with pre-enriched data.

Implementation of machine learning

Implementing AI means deciding on the right algorithm to be used to solve a specific problem. There are several algorithms, each with their own specialties. Figure 35 gives a good overview of the different kinds of machine learning algorithm groups that are currently being used with the possible fields that they are used in. Each of these groups consists of several possible algorithms. A selection must be made to determine which kind of algorithm could be used to solve the problem stated above. Most striking would be market basket analysis based on an unstructured association algorithm, customer segmentation on the basis of a clustering algorithm and optimized marketing on the basis of a reinforcement learning classification algorithm.

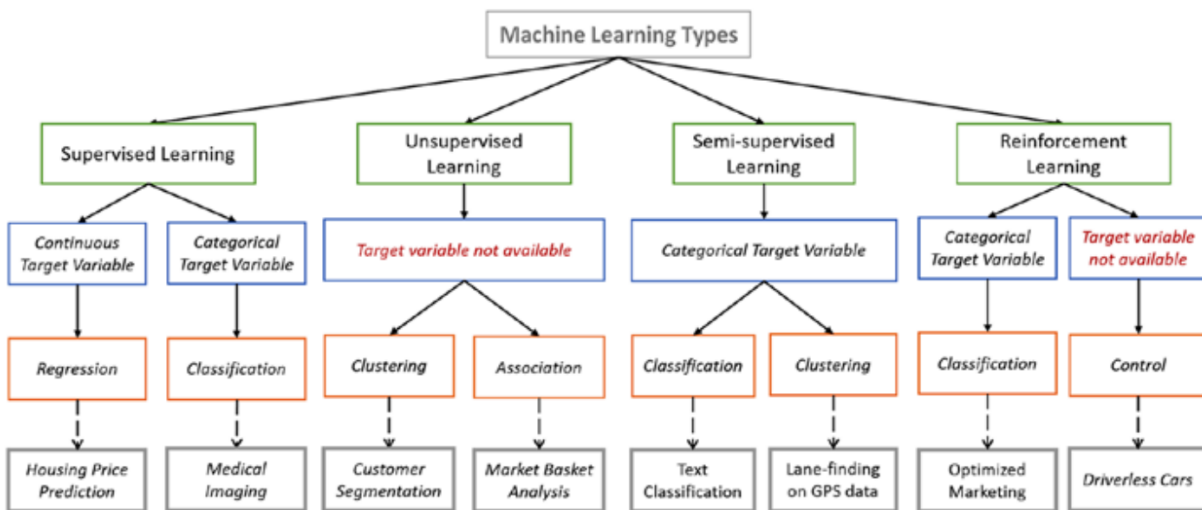


Figure 35 Different machine learning algorithms

E. Natural language processing

Coming to today's world that is the 21st century according to the industry estimates about 20 percent of the available data is present in the structured format (Shilakes & Tylman). Data is being generated as we speak as we treat as we send messages on for instance social media all through text messages. And most of this data exists in the textual form which is highly unstructured in nature. Too produce significant insights from the text data. It is important to know the techniques of text analysis.

Text mining and analysis

Text analysis and text mining refers to the process of extracting interesting and non-trivial patterns or knowledge from text documents regarded by many as the next wave of knowledge discovery, text mining has very high commercial values (Tan, 1999). Usually it is the process of deriving meaningful information from natural language text. involves the process of structuring the input text deriving patterns within this structure data and finally evaluating to interpret it. Output. Compared with the kind of data stored in database text is unstructured amorphous and difficult to deal with algorithmically. Nevertheless, in the modern culture text is the most common vehicle for the formal exchange of information. Now it mainly refers to the process of deriving information from text. this is done by the application of NLP.

NLP refers to the AI method of communicating with an intelligence system using natural language. By utilizing NLP and its components (Khurana, Koli, Khatter, & Singh, 2017). One can organize two massive chunks of textual data perform numerous automated tasks and solve a wide range of problems such as automatic summarization machine translation, named entity recognition, speech recognition and topic segmentation (Chowdhury, 2003).

There are several applications for NLP as described by Hurwitz & Kirsch (2018) . First, we have sentiment analysis. This field of NLP is commonly used. Second there is speech recognition. This technology of NLP is used for voice assistance like in google assistance or Cortana. Next, we have the implementation of chatbots. It uses an NLP to process the data enter and provides a response based on the input. Machine translation is also another use case of natural language processing. Considering the most common example here would be the Google Translate. It uses NLP and translates the data from one language to another and that too in real time. Other applications of NLP include spell checking. Keyword search which is also a big field with an NLP is used extracting

NLP is divided into two major components. That is the natural language understanding (NLU) and natural language generation (NLG) (Khurana, Koli, Khatter, & Singh, 2017). NLU involves tasks like mapping the given input into natural language into useful representations analyzing different aspects of the language. Whereas NLG is the process of producing the meaningful phrases at sentence in the form of natural language understanding a new language is very hard, there are a lot of ambiguity and that too in different levels. We have lexical ambiguity syntactical ambiguity and referential ambiguity. lexical ambiguity is the presence of two or more possible meanings within a single word. It is also sometimes referred to as semantic ambiguity. The second type of ambiguity is the syntactical ambiguity. In English grammar, this syntactical ambiguity is the presence of two or more possible meanings. Within a single sentence or a sequence of words. It is also called structural ambiguity or grammatical ambiguity. The final ambiguity is referral ambiguity. This ambiguity arises when we are referring to something using pronouns.

Information from any website or any document is also a use case of an NLP and advertised when matching for recommendation of the ads based on your history.

Khurana, Koli, Khatter, & Singh (2017) describe NLU to be divided again in several sciences as can be seen in Figure 36. Phonology is described as a sound, morphology is described as word formation, syntax is the science of language structure and semantics and pragmatics refer to understanding for semantics this refers to understanding sentences by pivoting on the interaction among worth-level meanings while pragmatics has the goal to of understanding and explaining how extra meaning is encoded in the text without it being encoded in them.

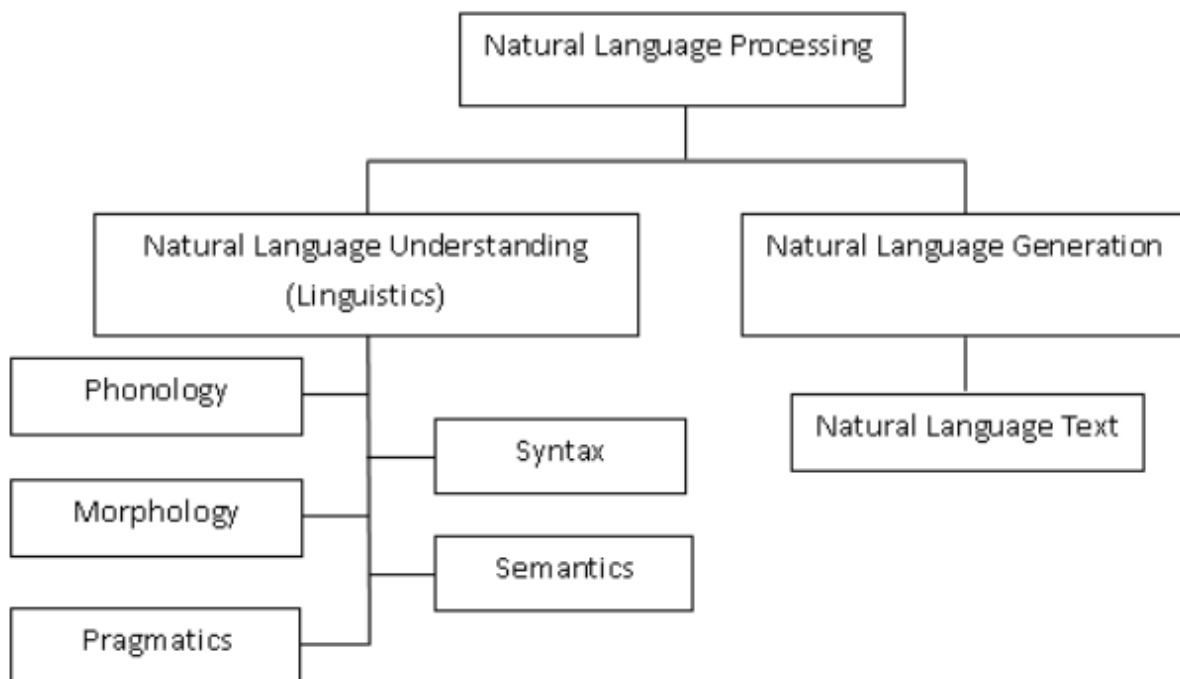


Figure 36 Broad Classification of NLP (Khurana, Koli, Khatter, & Singh, 2017)

Application of NLP

For this research the focus will be put on the understanding the given data, therefore the focus will be put on semantics. Possible application of NLP will be described.

Lexical semantics refers to understanding each word in a text for possible assignation of that word in a database with semantic classification. The ambiguity in lexical semantics might come from various meanings or senses of a word (Yu, 2012).

Named entity recognition suggest the recognition of names in the text. This suggest the recognition of names or places together with the type this name belongs too, in this case person or location reprehensively. One method of doing so is by checking what words are capitalized, however this would not suggest types as well as it would not recognize the first word in the sentence. Other ways of doing so is predetermining categories and assigning each word in the text to one of the categories. In this case the category for "none of the above" should be included. This method is used in the Hidded Makrov model described by Zhou & Su (2002).

Question answering is the use of NLP to determine the answer out of a question given in natural language. Questions are answered by querying the questions and locating documents that would be likely to contain the answer. Segments of the document are then given as the answer. The trick as described by Hovy, Gerber, Hermjakob, Junk, & Lin (2000) is to make the segments so small as to only contain the answer. The steps to question answering according to them are input question, parsing question, creating the query, retrieving documents, segment documents, rank segments, parse top segments, match segments against question and rank, rank and prepare answers and output answers accordingly. A representation of their steps is given in Figure 37.

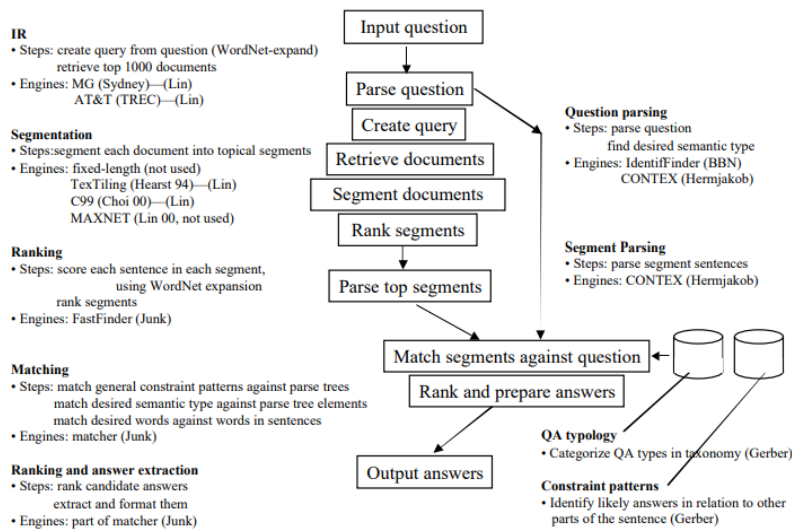


Figure 37 Webclopedia architecture (Hovy, Gerber, Hermjakob, Junk, & Lin, 2000)

Relationship extraction is an application of NLP in which the task is to detect and classify semantic relationships mentioned within textual data sets. An example of an approach is given by Ramakrishnan, Kochut, & Sheth (2006) who used a parsing structure to tag parts of speech and generate a parsing tree. The output is then converted into a main memory tree representation to show known entities, in their case medical terms from a database. The relationships between the entities are then identified by the parsing tree. Their goal was to extract related medical entities with each other using abstracts.

Sentiment analysis describes the use of NLP to identify affective states by extracting subjective information. The fundamental technology behind sentiment analysis is the classification (Pang & Lee, 2008). Still there are multiple approaches to sentiment analysis which could be grouped in four main categories: keyword spotting, lexical affinity, statistical methods, and concept-based techniques.

Keyword spotting classifies data by affect categories based on the presence of unambiguous words such as happy and sad. Although sometimes affective, this approach is said to be weak because it can't reliably recognize affect negated wording as well as it only relies on surface features.

Lexical affinity is an enhancement on keyword spotting in which obvious affect words are spotted and linked to a probable affinity. These probabilities are usually trained and predefined. Lexical affinity is however not able to properly analyse negated sentences or sentences in which the affect words have a different meaning.

Statistical method approach depends on a machine-learning algorithm to learn a data set containing for instance past reviews. However statistical methods are said to generally be semantically weak and only work when fed with a sufficiently large database.

The concept-based approach uses semantic network for text analysis. In doing so, the system can grasp conceptual and affective information out of the data by relying on large knowledge basis. The system is therefore able to find subtly expressed sentiments. It is however dependent on the knowledge basis it is using (Cambria, Schuller, Xia, & Havasi, 2013).

Note however that intelligence 2.0 as described in this research should not be misinterpreted as the machine learning powered predictive aspect of intelligence. Although this is also progress being made in the field of intelligence systems (Koch, 2015), the scope of this research is on the ability to analyze unstructured data.

F. B2B marketing structure and marketing activities of the case firm

Marketing structure

The marketers of the case firm are involved in the promotion of the services that are available. The sector-based marketers and account executives focus on a specific set of accounts. The accounts can be split in 3 categories: normal accounts, top accounts, and corporate managed accounts (CMA's). The country board decides on which account to be placed in which category. The main difference between the latter two categories is stated to be the budget. More sales and marketing effort is done towards the more promising CMA's. The account executives are each responsible for a CMA. They are tasked with setting up and executing an annual custom-made plan. The account-based marketers provide so called vertical marketing efforts

The accounts are also divided in sectors. These sectors are determined based on the activities of the accounts. Accounts with similar activities or objectives are placed within the same sector. The sector based marketers are responsible for the marketing activities of top accounts and CMA's within a specific sector. Because these accounts have common goals, the marketing activities towards these accounts are usually similar. By focusing on one specific sector, the sector marketers can deliver custom made marketing activities that can be used on all accounts.

Next to the vertical marketing activities, there are the offshore portfolio marketers. The portfolio marketers use a more traditional approach to marketing. These marketers also promote services but are specialized in one specific set of services that they promote towards a wider range of accounts. These marketers provide horizontal marketing efforts. These efforts sometimes overlap with the sector-based marketers, but their spectrum goes broader to also other accounts than CMA's and top accounts.

Together they form an organizational matrix structure as defined by R.Galbraith (1971). The structure combines the use of a structural approach with a project-based approach and takes advantage of the positive attributes of both. So, does Gottlieb (2007) address the ability to deliver work across business more efficiently, the ability to respond more flexibly and the break of the business information silos as advantages. The latter of which suggest the need and possibility of good communication and cooperation that will be stimulated using such an organizational structure. In Figure 38 an overview is given of the matrix structure as used by the case firm. So, do the portfolio teams target horizontally, and do the account teams and sector teams target vertically.

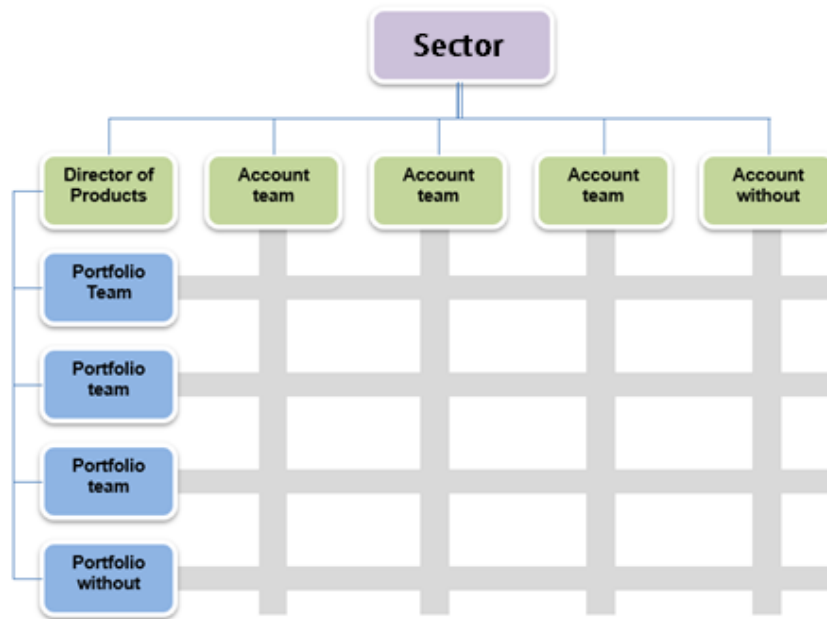


Figure 38 Matrix structure marketing case firm

Marketing activities

One of the team's main purpose is the promotion of the services. The promotion builds by several marketing activities. First there is marketing planning, the creation of a marketing plan is that lasts a year and is aiming to fortify or change the positioning of the organization. The two marketing activities that are being planned are: general daily marketing activities and marketing activities specific toward an opportunity. The latter is called pursuit marketing activity. This type of marketing activity includes all activities to support the account team toward winning a qualified opportunity. During and RFP or a tender, rules are usually included to prohibit certain marketing and communication strategies towards decision makers. These rules are usually presented in the RFP itself. Marketers are thus tasked to market in a certain way. Therefore, as soon as an opportunity is discovered until the RFP is officially released, the marketers should try to market and influence as much as possible. After the RFP is released, the marketing activities are reduced to whatever is still allowed. A conclusion could therefore be that the awareness phase before the buyer journey is established might be of the greatest importance for marketing the services. Finding these opportunities earlier, and thus stretching the awareness time phase's time window can thus result in more possible marketing activity and thus an increased chance of winning the deals.

Marketing personalization makes sure customers give higher value to the cause, become more profitable for the business (Montgomery & Srinivasan, 2002). The marketing team tries to personalize by using information placed in their CRM-system. CRM has become a major technology marketing as already prognosed by Kalakota and Robinson (1999). At its core, CRM is about acquiring customers, knowing them well, providing services and anticipating their needs (Goodhue, Wixom, & Watson, 2002). Within the Capgemini account teams the information about the clients should be put in the CRM-system by the account team. The CRM system thus functions as an database. Next to that the CRM system also functions as a medium for internal communication between the account team members.

In his findings, Pai (2011) found whether or not users feel the CRM system is helpful in doing the job; whether the system is easy to use, what exactly will be profitable conditions in the environment; whether each task can benefit each other, were all key factors to influence user's acceptance of the system. From observation and according to the team the CRM system is not filled in properly to be used to its full efficiency. The system, as it is used right now, is said to be too complicated. Employees might lack knowledge on how the system can be used to its full potential. Another reason might be that employees don't understand the added value of the filling in the system. They might think filling in the system is not worth the time, especially since it can be time consuming if the general know-how is missing and education can also take a lot of time. As a result, the CRM system is not updated, which leads to less efficient use of the system.

G. GDPR

In December of 2015 the expected a long-expected regulation was finally provisionally agreed upon. The final details of the General Data protection Regulation (GDPR) where being decided upon and publication of the rules was decided to be scheduled for July 2016 (Tankard, 2016). On May 25th 2018 the moment was then finally there. The EU's data protection act dating from 1995 was succeeded by the GDPR and becomes enforceable across Europe, including the UK (Digital boost, 2018). The main goal of the implementation of the GDPR was to give control to individuals over their personal data and to simplify the regulatory environment for international businesses by unifying the regulation within the EU (Council of the european union , 2015). Neglecting these new regulations, firms may be fined up to 10% of their worldwide revenue. This could have major consequences for companies. (Council of the european union , 2015).

For Individuals this implied change as well information and access (to know that their personal data is being processed and have access to this data free of charge), data portability (data collected under certain circumstances must be provided "in a structured, commonly used, and machine-readable for), rectification (ability to correct inaccurate personal data or to complete information), erasure (also known as the "right to be forgotten," applicable only under certain circumstances), restriction (individual may restrict data controller from processing data further under certain circumstances).and objection (to object to processing of one's data) (Cox, 2018).

The GDPR is described to have tighter implications toward the collection of data, the ways you use the data, the ways you store the data and the way you share data. The GDPR for example bring the need for a technical and organizational measure to be in place for controllers of personal data, processes that would handle personal data should be built with consideration of data protection so that it is not available to publicity without consent, and personal data may not be processed unless under a lawful bases or with affirmation of consent from the data supplier (Kerins, 2018). Other lawful grounds for data processing are: if it is necessary for the performance of a contract with the subject or to take steps to enter into a contract, if processing is necessary for legal obligation, if processing is vital to the interests of the subject, if processing is necessary for a task carried out in the public interests, or if legitimate interests are pursued (i.e. the processor has a stake in the matter such as in the case of direct marketing and relationship building) (Davis, 2017).

H. Sumerized literature table for intelligence system implementation

The table below shows a summary of literature on intelligence system. The literature is summarized and ordered according to the layer its content is referring to. In this table, the challenges for implementation are also included for each layer.

Table 5 Sumerized literature for intelligence system implementation

Intelligence system layers	Forms	Description	Challenges for implementation	General success factors for implementation
Sources	Early intelligence	- Knowledge management sources - o Human capital as a source for intelligence by training and making them aware of the necessity of sharing knowledge (Festervand, Grove, & Reidenbach, 1988) - o Ad hoc ongoing of projects both internal and from competitors in the form of summaries (Prescott, 1995) - o Physical observation of the customer/competitor (Kotler & Keller, 2012) - Online transactional process systems (OLTP) for recording facts that are important to the business, quantitative internal data (Yeoh & Koronios, 2010). - o Accounting and transactions: Accounting and transactional data could be analyzed and presented in the form of reports to help employees get a grip on how business was going (Davis & Olson, 1985)	Success on the availability of sources and intelligence of the human capital. Training of the human capital can help in extracting more intelligence. (Festervand, Grove, & Reidenbach, 1988; Wright & Calof, 2006)	Finding the intelligence needs of the practitioners to scope the implementation efforts (Yeoh & Koronios, 2010). Focus will make it able to more efficiently use scarce resources for greater efficiency. Two overall methods are found for gathering the intelligence needs: - KIT model (Herring, 1999). - Johari window. (Weiss & Wright, 2006) . Establishing the available data sources: In order to establish a good intelligence system, the data sources that are available should be indicated. By establishing what data sources are available and what intelligence could be extracted from these data sources. Given data sources should be divided in structured and unstructured since that is the determining factor between intelligence 1.0 and intelligence 2.0. Furthermore the data should be checked on quality to ensure the quality of the intelligence coming out of the intelligence system (Bean, 2011).
	Intelligence 1.0	- Sensor data: This data can be analyzed to extract features and identify anomalies and hazardous events. (Tang, et al., 2017) - Market data (Lei & Moon, 2015) - Business and system transactions (Ali, Nassif, & Capretz, 2013) - System records (Watson & Wixom, 2007) - o Customer relationship management database - o Enterprise resource planning database - o Supply chain management database - Registers (Sale, Patil, & Thube, Crime Prevention with Data Warehouse using OLAP through Business Intelligence, 2018)	The availability of sources is key to implementing a data driven intelligence system (Nemec, 2012). The quality of the data is a success factor to the intelligence. (Garbage in is garbage out) (Watson & Wixom, 2007)	Establishing how intelligence should be presented: The intelligence should presentation should be clear to the practitioners. Successful usage will only be established if the intelligence is presented in a clear way to the practitioners. Therefore the practitioners can help in defining how they would like to have added intelligence (Watson & Wixom, 2007) . In order to determine what kind of storage is needed, The question should be raised as to how up to date the intelligence is expected to be.
	Intelligence 2.0	- User generated content from web 2.0 (Francia, Gallinucci, Golfarelli, & Rizzi, 2016; Schneckenberg, 2009) - o Social media content (Meire, Ballings, & Van den Poel, 2017) - o Blogs and forums (Abdelmoety & Gounaris, 2015) - Reports and research papers, media, surveys. (Negash, 2004)	Availability of sources: Whether the data is openly available (Bean, 2011). Validity of the sources: sources are not peer reviewed and can therefore be biased and lack validity. If grey data is used, users should be aware of the validity problem (McAuley, 2000; Gong, Cho, & Lee, 2018). Relevance of the data: whether the data contains the right information (Cortez & Johnston, 2017)	

Data extraction	Early intelligence	- Knowledge management systems - o Collection of data ▪ Going into the field to gather intelligence by monitoring activity of the market environment (Kotler & Keller, 2012). ▪ Human capital reporting (Festervand, Grove, & Reidenbach, 1988) - Mainframe based systems (single variable) systems. (Power D. J., 2007) - o Collection of data ▪ OLTP data extraction (Baars & Kemper, 2008)	Success dependent the training and awareness of human capital to share the intelligence. Low complexity of mainframe based intelligence, success is dependent on relevance of the intelligence. (Festervand, Grove, & Reidenbach, 1988; Wright & Calof, 2006)			
	Intelligence 1.0	- Collecting data: - o Extract transform and load technology for extracting data from several sources (Chen, Chiang, & Storey, 2012) - o OLTP data extraction for transaction (log) data from a source.	Implementation of the right extraction technique to derive intended impact is dependent on careful analysis of the application of the intelligence system together with the practitioners. (Chen, Chiang, & Storey, 2012)			
	Intelligence 2.0	- Collection of unstructured data unstructured data ▪ Text mining /Natural language processing technology (Chen H. , 2010) - o Sentiment analysis (Bai, 2011) - o Relationship extraction (Chen H. , 2010)	The method of extraction is dependent on the desired outcome of the intelligence system and thus the intelligence need (Sun & Wang, 2015).			
Data storage	Early intelligence	- Storage of information in human capital (usually managers) (Festervand, Grove, & Reidenbach, 1988) - Tables and spreadsheets (Cottrill, 1998).	The manager is the key person for the intelligence. He has to have ta capability to remember all that is told (Festervand, Grove, & Reidenbach, 1988)			
	Intelligence 1.0	- Operational or transactional databases - Data lakes (Botelho, 2018) - Data warehouses - o Relational data base management systems (RDBMS) (Chaudhuri, Dayal, & Narasayya, 2011) - o Multi-dimensional databases (OLAP cubes) (Bălăceanu, 2007)	Dependent on the structure of the data, need for up to date (real time) intelligence, the need for inclusion of historical data. Therefore it is dependent on the needs of the practitioners.			
	Intelligence 2.0					
	- Addition of Data marts (Watson & Wixom, 2007)					
Data usage	Early intelligence	- Evaluation is done by management and converted into marketing strategies. It is based on the management perceived importance and usefulness (Festervand, Grove, & Reidenbach, 1988) - Intelligence systems involved limited (if any) analysis (Prescott, 1995)	The challenge of analysis is dependent on the capabilities of the manager.			
	Intelligence 1.0	- Online analytical processing (OLAP) (Chaudhuri, Dayal, & Narasayya, 2011) - Filtering , aggregation and drilling down - Data mining: Data mining is the automated process of discovering previously unknown useful patterns in data (Bălăceanu, 2007) - o Neural networks for pattern finding exploration (Larson & Chang, 2016) - o machine learning. Classification/prediction and clustering with generic algorithms (Larson & Chang, 2016) ▪ Advanced analysis makes it possible to analyze a multitude of variables (Lei & Moon, 2015) ▪ Due to advanced analysis, using data for predictive possibilities arise (Larson & Chang, 2016)	Depending on the kind of knowledge needed (analysis or descriptive) and the scope of the knowledge			
	Intelligence 2.0					

Intelligence presentation	Early intelligence	- Visualization of several sources and trough structuring (Ram & Carlson, 1990) - Visual sumeries (Reinschmidt & Francoise, 2000):	Intelligence should be given clearly and understandable to the users. Best way to do so is to include users in how they want intelligence to be presented.	
	Intelligence 1.0	- Fixed scheduled reporting (Bălăceanu, 2007) - Ad hoc query reporting (Chaudhuri, Dayal, & Narasayya, 2011)	Users will only rely on intelligence that they trust. The intelligence should thus be represented in a clear way, and users should be trained in the analysis and sources of the intelligence (Watson & Wixom, 2007)	
	Intelligence 2.0	- Visual dashboarding for tracking KPIs - Rapid ad hoc visualization for patter recognition - Relational graphs (Petermann, Junghanns, Müller, & Rahm, 2014) - Intergrated in another intelligence system dashboard (Lawton, 2006)		