2012

Enterprise Analytics Adoption Model:

an exploratory study in transforming an organization towards analytical competitor

Image source: www.accenture.com

Delft University of Technology
Faculty of Technology, Policy and Management

Master of Science in Management of Technology
MOT2910 Master Thesis 2011/2012

Delft, 14th September 2012

GRADUATION COMMITTEE

Prof. dr. Yao-Hua Tan
Chairman
Section of Information and Communication Technology

Dr. ir. Jan van den Berg
First Supervisor
Section of Information and Communication Technology

Dr. ir. Zenlin Kwee
Second Supervisor
Section of Economics of Innovation

Drs. Olaf Penne
External Supervisor
Accenture Netherlands

AUTHOR
M.R. Natadarma [1203819]
meriane.natadarma@gmail.com

TU Delft
Technische Universiteit Delft

ACKNOWLEGDMENT

This thesis covers the development of a conceptual Enterprise Analytics adoption model, or denominated as the ADOPT-model, to facilitate organizations in developing their analytical capabilities. This presents the results of my research graduation project to achieve a Master of Science degree through the program of Management of Technology at Delft University of Technology. The research project was initiated by doing an internship at a consultancy company, Accenture in Amsterdam.

I would like to thank Accenture for giving me the opportunity to conduct my research project in their professional environment. Many thanks to all supporting and helpful inputs I got from the people who work there. In particular, I would like to thank my external supervisor, Olaf Penne, who gave me wise advices in getting used to the company's culture and who helped me mainly with networking to other professionals.

Also I would like to thank greatly to my first supervisor, Jan van den Berg, who guided me during my entire research and supported me continuously in what I am doing and believe. All our conversations have opened my eyes to conduct the research project in 'my way' of doing research, not others. Not to miss out, I really appreciate and thank for the feedback and proof-reading from my second supervisor, Zenlin Kwee.

I would like to thank my supportive husband who always believe in me to achieve my own goals, and I thank my beautiful children as well, as they always cheer me up and be the sun shine in my heart. Last but not least, I greatly thank God for giving me the courage and energy to finish my Master program in two years despite my other responsibilities. Without His blessings, I will never be able to reach the achievements I have until now.

Meriane Natadarma

Delft, 14 September 2012

This work is dedicated to my family, my precious son and daughter, my beloved husband, and specially to the Greatest of all.

Enterprise Analytics Adoption Model:
An exploratory study in transforming an organization towards analytical competitor

ABSTRACT

Business Intelligence- and Analytics solutions offer business users to gain a competitive advantage against their peers in the dynamic economic situation. A compelling characteristic of an enhanced BI-solution is distinguished by the adoption of advanced Analytics in business activities to obtain information more easily, to gain more insights in company's data, and to get more timely and better decision-making support. However, many organizations are still reluctant to adopt Analytics in their organizational structure, culture and mainly to carry out their business activities. For organizations that tend to have corporate culture based on silos, the implemented Analytics are not yet efficiently and effectively utilized and they tend to have concerns in data governance across organization. During the execution of the research project, the common Analytics adoption process was explored and subsequently an Enterprise Analytics adoption model, or denominated as the ADOPT-model, was developed. The conceptual model was designed to provide an overall overview and guidelines for organizations to pamper their Analytics initiatives emerged across various functional units. A holistic approach at the enterprise level has been opted to achieve a consistency of effectiveness across business units within an organization by focusing on the four organizational elements, i.e. structure, process, people, and technology. Accordingly, the main research question was formulated as follows: "how to transform an organization towards an analytical competitor?". The conceptual ADOPT-model was designed to provide a better representation of the exploration study, as well as to structure the research findings in answering the research (sub-)questions. A research framework was built to provide a systematic and a clear overview for the execution of research project. Desk research and literature study were carried out in the early stage of project execution; subsequently a primary data was collected by conducting qualitative interview sessions with the field experts and relevant stakeholders. All data gathered was analyzed by utilizing the Applied Thematic Analysis approach and a thorough analysis results were explained by illustrating various key nodes and relationships of the themes in the thematic networks. The reflections on the research findings, the quality of the results, as well as a brief reflection on the entire process, were reported. Finally, the conclusions drawn from the data analysis and the recommendation for practitioners were formulated, and then followed by the limitation of the research and the direction for possible further research at the end of this thesis.

***Keywords**: (Enterprise) Analytics, Predictive Analytics, Business Intelligence, Business Operating Model, Competitive Advantage*

LIST OF FIGURES

Figure 1. Four traits required from a company to achieve wide adoption of analytics 3
Figure 2. The primary obstacles to widespread adoption and use of information and analytics in organizations (LaValle et al., 2010) 4
Figure 3. Based on 857 responses from 179 respondents (4.8 average responses per respondent) (Russom, 2010) 5
Figure 4. Accenture's Operating Model Framework (Langlinais, Peterson, & Peters, 2008)................. 8
Figure 5. Research framework adapted from (Hevner et al., 2004) 9
Figure 6. Thesis systematic outline 12
Figure 7. Evolution in BI semantic (Eckerson, 2011b) 17
Figure 8. The more sophisticated intelligence of an organization, the greater competitive edges can be reached (Davenport & Harris, 2007). 19
Figure 9. Market performance of Analytical companies compare to S&P 500 index 22
Figure 10. World GDP growth rate (Economist, 2012).. 22
Figure 11. Better decisions and improved outcomes powered by Analytics (Accenture, 2012) 26
Figure 12. Analytics' scope of analysis regarding different types of industry..................................... 28
Figure 13. Preliminary design of ADOPT-Model.. 37
Figure 14. Initial design of ADOPT-model 38
Figure 15. Steps taken in the textual analysis in ATA approach.. 48
Figure 16. Thematic network for Analytics adoption in various areas.. 52
Figure 17. Thematic network for desired Analytics capabilities 53
Figure 18. Thematic network for major Analytics vendors 55
Figure 19. Thematic network of vendor selection factors 57
Figure 20. Thematic network of Analytics organizations' typical traits 59
Figure 21. Thematic network of perceived challenges in organizational Structure............................ 61
Figure 22. Thematic network of perceived challenges in organizational Processes........................... 62
Figure 23. Thematic network of perceived challenges in People organization 63
Figure 24. Thematic network of perceived challenges in term of Technology 64
Figure 25. Critical phase in term of Structure 65
Figure 26. Critical phase in term of Process 65
Figure 27. Critical phase in term of People 66
Figure 28. Critical phase in term of Technology.. 66
Figure 29. Verified model in organizational Structure 68
Figure 30. Verified model in organizational Process 69
Figure 31. Verified model in organizational People 71
Figure 32. Verified model in organizational Technology... 72
Figure 33. Complete representation of verified ADOPT-model 74
Figure 34. Operating model environment... 93
Figure 35. Curach Consulting’s Business Operating Model Review 94
Figure 36. PwC's Operating Model Framework... 94
Figure 37. Davenport's analytics maturity model 95

LIST OF TABLES

Table 1. Description of each adoption phase 37
Table 2. Selection criteria for consultant-respondents 42
Table 3. Selection criteria for client-respondent 43
Table 4. Interview respondent list 44
Table 5. Interview's themes 45
Table 6. Critical success factors in adopting Analytics 85

LIST OF ABBREVIATIONS

ADOPT	: Analyze, Define, Own, Prepare, Transform
ATA	: Applied Thematic Analysis
BA	: Business Analytics
BI	: Business Intelligence
CRM	: Customer Relationship Management
DDBMA	: Distributed Database Management System
DSS	: Decision Support System
DW	: Data Warehousing
EA	: Enterprise Architecture
EAAM	: Enterprise Architecture Adoption Model
EIS	: Executive Information System
ERP	: Enterprise Resource Planning
IS	: Information System
IT	: Information Technology
KMS	: Knowledge Management System
KPI	: Key Performance Indicator
OLAP	: On-line Analytical Processing
SCM	: Supply Chain Management
QDA	: Qualitative Data Analysis

TABLE OF CONTENTS

ACKNOWLEGDMENT .... **i**
ABSTRACT .... **v**
LIST OF FIGURES .... **vii**
LIST OF TABLES .... **viii**
LIST OF ABBREVIATIONS .... **ix**

Chapter 1. INTRODUCTION **1**

1.1 Rationale behind the Research Project 1
1.2 Research Context 1
1.2.1 Research Problems 3
1.2.2 Research Objective 5
1.2.3 Research Questions 6
1.3 Research Design 7
1.3.1 Research Methodology 7
1.3.2 Research Framework 8
1.3.3 Data Collection Instrument 10
1.3.4 Analysis Tool and Technique 10
1.4 Relevance of the Research 10
1.4.1 Scientific Relevance of the Research 10
1.4.2 Practical Relevance of the Research 10
1.5 Structure of the Thesis 11

Chapter 2. ENTERPRISE ANALYTICS DOMAIN **15**

2.1 Introduction 15
2.2 What is Analytics? 15
2.3 Emergence of Analytics 16
2.3.1 Types of Analytics 19
2.4 Analytics Market and Trends 22
2.4.1 Global Economic Shift 22
2.4.2 Need for Analytics and Data-Driven Decision Making 23
2.4.3 Analytics as a Path to Better Decisions 24
2.4.4 Trends 26
2.5 Opportunities and Challenges 27
2.5.1 Opportunities 27
2.5.2 Challenges 28
2.6 Summary 29

Chapter 3. OPERATING MODEL ONTOLOGY **31**

3.1 Introduction 31
3.2 Sustainable Competitive Advantage 31
3.3 Operating Model as Corporate Alignment 32
3.4 General Objectives 33

3.4.1 The “as is”- and “to be”- states 34
3.4.2 Dialogue between Business and IT Sides 34

3.5 Summary 34

Chapter 4. ENTERPRISE ANALYTICS ADOPTION MODEL **35**

4.1 Introduction 35
4.2 Conceptual Design 35

4.2.1 What is Enterprise Analytics Adoption Model? 36
4.2.2 Initial Design of ADOPT-Model 36
4.2.3 Value Propositions of ADOPT-Model 40

4.3. Summary 40

Chapter 5. DATA COLLECTION & ANALYSIS APPROACH **41**

5.1 Introduction 41
5.2 Qualitative Approach Using Interviews 41

5.2.1 Rationale behind Interview Methodology 41

5.3 Respondents Selection 42
5.4 Operationalization 45
5.5 Data Management 46
5.6 Data Analysis Approach 46

5.6.1 Applied Thematic Analysis 47
5.6.2 Thematic Networks 47

5.7 Summary 49

Chapter 6. RESEARCH RESULTS AND ANALYSIS **51**

6.1 Introduction 51
6.2 Analytics Market Situation 51

6.2.1 Analytics Adoption Areas 51
6.2.2 Desired Analytical Capabilities 52
6.2.3 Major Analytics Vendors 54
6.2.4 Vendor Selection Factors 56
6.2.5 Typical Traits of Organizations Considering Analytics Adoption 58

6.3 Adoption Process Evaluation ... 60

6.3.1 Perceived Adoption Challenges in term of Structure ... 60
6.3.2 Perceived Adoption Challenges in term of Process ... 61
6.3.3 Perceived Adoption Challenges in term of People ... 62
6.3.4 Perceived Adoption Challenges in term of Technology ... 64
6.3.5 Most Critical Adoption Phases ... 65

6.4 Verification of ADOPT-Model ... 67

6.4.1 Organizational Structure ... 68
6.4.2 Organizational Process ... 69
6.4.3 Organizational People ... 71
6.4.4 Organizational Technology ... 72

6.5 Summary ... 75

Chapter 7. REFLECTION ... 77

7.1 Introduction ... 77
7.2 Reflection on Research Results ... 77
7.3 Quality of the Results ... 78

7.3.1 Reliability ... 78
7.3.2 Validity ... 79

7.4 Reflection on Research Process ... 79

Chapter 8. CONCLUSIONS AND RECOMMENDATIONS ... 82

8.1 Introduction ... 82
8.2 Research Findings ... 82
8.3 Recommendations for Practitioners ... 85
8.4 Research Limitation ... 85
8.5 Direction for Future Research ... 86

REFERENCES ... 88

APPENDIX A. Research Project Timeline ... 92
APPENDIX B. Typology of Various Operating Models ... 93
APPENDIX C. Analytics Related Framework ... 95
APPENDIX D. Interview Invitation Letter ... 97
APPENDIX E. Interview Protocol for Consultants ... 98
APPENDIX F. Interview Protocol for Clients ... 102
APPENDIX G. Follow-up Interview Letter ... 106
APPENDIX H. Applied Thematic Analysis Coding ... 107

Chapter 1
INTRODUCTION

"There will be hunters and hunted, winners and losers. What counts in global competition is the right strategy and success."
~Heinrich von Pierer (1941)

1.1 Rationale behind the Research Project

The purpose of this research project was to accomplish a Master of Science degree for a specialization program in Management of Technology at the Technical University of Delft. The research project was conducted in a practical research environment during the internship within a company in the duration of seven months. This company was a global management consulting, technology services and outsourcing company, Accenture, located in Amsterdam. Daily research activities were carried out mainly at the university and at the company site within the department of Process and Information Management (P&IM), which was a subdivision of the Technology Growth Platform (TGP). This corporate subdivision provided diversified solutions around Business Intelligence's body of knowledge and techniques, business processes, functional and technical solutions for its customers in order to deliver high performance. Overall, the research project was conducted under both academic supervision from the university, and practical supervision from the company.

The structure of the first chapter is outlined as follows; the research context described in Chapter 1.2 comprises the research problem, objective and research (sub-) questions. The chosen research methodology is discussed in Chapter 1.3, and then followed by Chapter 1.4 that covers the research relevance within scientific and managerial perspectives. At the end of this chapter, the outline of the remaining contents of the thesis is presented in Chapter 1.5. In addition, the entire research project timeline starting from the New Hire days at Accenture, the kick-off and green-light meetings with the graduation committee, until the delivery of this final thesis can be found in Appendix A.

1.2 Research Context

Many companies across different industries offer similar products or services and use similar technology. These companies compete on their remaining points on differentiation within diverse business processes (Davenport & Harris, 2007). Previously, the competition was based on the geographical advantage or protective regulation such as intellectual property etc. Due to the economic globalization, this kind of distinctive advantage has been eroded and companies are still anticipating to innovate for another differentiation manner in order to gain competitive advantage, grow revenues and reduce costs (LaValle, Hopkins, Lesser, Shockley, & Kruschwitz, 2010). Business Intelligence (BI) - solutions with Analytics capabilities open the gate to new basis for competition by providing effective and efficient solution to obtain information easily, better insights within business processes, better and more timely decision-making support.

As Gartner has forecasted the global BI and Analytics market to grow 9.7 per cent to reach US$ 10.8 billion in 2011, the growth over the forecast period to 2014 is expected to slow down slightly with the high single digits remained. Despite of the global economic recession, the market for BI platform will still be one of the fastest growing markets for software in most regions. Likewise, according to Gartner's annual global CIO survey published last year, BI and Analytics were ranked as number five on the 10 top list of technology priorities for Chief Information Officers (CIOs) (Gartner, 2011). More and more companies are realizing the benefits offered by BI and Analytics, however not every company is adequately convinced to move forward with BI or Analytics, and its implementation is still very limited within a certain line-of-business in organization. Therefore another approach is requisite to support the widespread adoption of, especially, Analytics in Medium-to-Large Enterprises. Correspondingly, this research report is constructed to explain thoroughly the exploration of Analytics adoption problem encountered within this research context.

As aforementioned, BI-solutions with Analytics capabilities can help companies to gain better insights into their business and to support decision-making at strategic-, operational- and tactic level. While *strategic managers* employ them for identifying market opportunities, products launch decision and positioning, and competitive intelligence. *Tactical managers* employ them to support decision in the areas of sales forecasting, customer acquisition, retention and extension purposes, direct marketing and marketing campaign analysis. And *operational managers* employ them to support decisions regarding better utilization of facilities or supply chain management (Bose, 2009). Business Analytics (BA) leads to the optimization of the use of their resources, more room of possibilities, revenue growth, cost reduction and better risk management. By Analytics is meant as a subset of BI that uses data extensively, statistical- and quantitative analysis, explanatory- and predictive models, and fact-based management to steer decisions and guide actions (Davenport & Harris, 2007). Concerning the value propositions offered by Analytics, companies are able to achieve competitive advantage towards their competitors.

A research conducted by MIT & IBM in 2010 enquiring 3000 executives, managers and analysts across 30 different industries and 108 countries, has investigated the relationship between the company's performance and its Analytics ability (LaValle, Hopkins, Lesser, Shockley, & Kruschwitz, 2011). The research showed that Analytics-leading organizations are three times more successful than Analytics-starter organizations. Top performers prefer five times more for data-driven decision making approach than intuitive-driven. This research has concluded that neither the quality of data nor the financial support is the main factor that hampers the entrance of Analytics but rather the *organizational boundaries*, which will be described in section 1.2.1 of the research problem.

Based on the findings from several companies studied, four attributes were proven to be present in the true analytical competitors whereas less advanced organizations may have only one or two at best (Davenport & Harris, 2007). An organization must *have support of an important and distinctive capability*, *approach Analytics in Enterprise-level*, *hold the commitment from the senior management level*, and *have the large-scale ambition*. The four primary attributes were seen as the foundation pillars supporting an analytical platform. They are interrelated to each other and there will be difficulties to reimburse others when any one is absent. Affirming this idea, Deshpande (2011) has claimed that there exist strong interconnections between those attributes with the feedback loops and causal relationships, as depicted below in Figure 1.

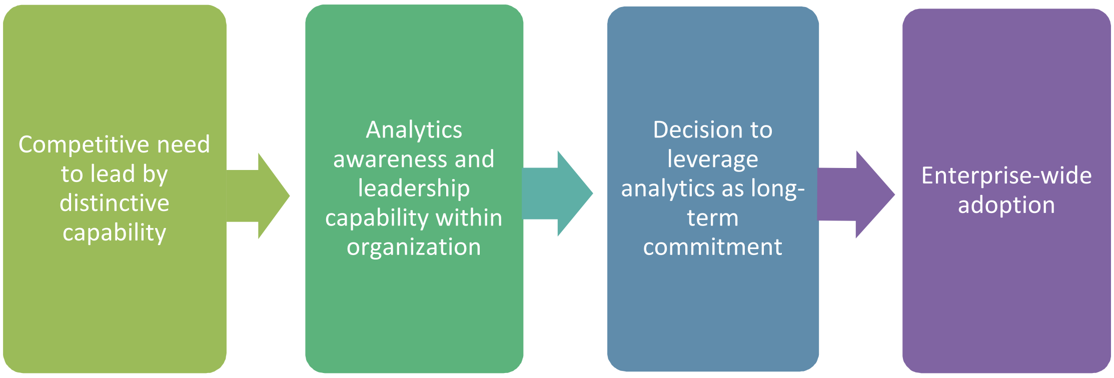

Figure 1. Four traits required from a company to achieve a wide adoption of analytics

- The first trait is that company's need for Analytics emerges from competitive need to lead with its distinctive capability. Due to Analytics adoption, a distinctive capability can be sharpened for the company to be able to differentiate itself in the market place and gain the competitive advantage.
- Analytics awareness within the organization and Analytics leadership capability are essential to the deployment towards Analytics. A broad adoption of analytical approach for business processes demands changes in organizational culture, process, behavior and skills for numerous employees.
- The transition process to achieve mature organizational capabilities needs a long-term commitment from the senior executives, which is also aligned with the business strategy. In this manner, the organizational "buy-in" is necessary to be obtained.
- The next step would be the adoption of Analytics across organizations without imbalance of specific business unit is being optimized by Analytics at the expense of another, unless it is crucial from the strategic perspective. This leads to the realization that requires more than localized adoption in one or two business unit(s) or function(s) or department(s), hence on enterprise-wide adoption. Last trait constitutes an organization to practice their business activities by a holistic data-driven approach that shapes a strong Enterprise Analytics capability.

1.2.1 Research Problems

According to Accenture, many organizations are still reluctant to implement Analytics solutions within their business activities, in which the adoption of Analytics is hampered. The *key business needs* of organizations and the *key challenges* entailed in the Analytics adoption at enterprise level are accounted for the foundation of the study proposition, whereas each proposition generates vigilance to something that should be examined within the scope of study (Yin, 2009). These key challenges are concisely described in the subsequent paragraphs.

Awareness of Analytics' Value Propositions

Many organizations are still unaware that Analytics can set the pace for their business operations. Organizational faulty realization of cost-benefit analysis and immature knowledge of Analytics tend to shove away the fact-driven decision making approach. The result of a research collaboration from MIT & IBM in Figure 2 has showed that the primary obstacle to a widespread Analytics adoption in organization is due to lack of understanding on how to utilize Analytics to improve the business (LaValle et al., 2010). This unawareness was also verified by the (senior) managers interviewed during the initial problem analysis at Accenture. Some of their customers have undergone the development of Proof-of-Concept (PoC) and yet those companies still doubt to take a step to move forward with Analytics.

Figure 2. The primary obstacles to widespread adoption and use of information and analytics in organizations (LaValle et al., 2010)

Organizational boundaries

In spite of the common perception, the most challenging Analytics adoption faced by organizations are managerial and cultural rather than related to data and technology (LaValle et al., 2011). This happens based on their existing corporate culture, organizational structure and skills. The top two potential barriers in coordinating multiple data management in practice are due to corporate culture based on silos, and the data ownership across organization as shown in Figure 3.

Still many companies use data in internal silos, where data are gathered, executed and analyzed within same business functions or business units. In contrast, organizations can create an agenda that makes Analytics as the core to business strategy and operations by integrating data from silos and disseminate data across the enterprise (Kiron, Shockley, Kruschwitz, Finch, & Haydock, 2011). According to Gartner prediction, a distinctive organizational model, centralized or decentralized, will be the basis of BI initiatives by 2013. Applying the analytical resources only to serve departmental needs is lacking of consistency in terms of data definitions and measures across the entire organization (Gartner, 2012). However, by focusing too much on the speed by which the transformation is introduced, organizations often stumble in integrating the data and a different way of working into existing organizational structure and knowledge. In this way, moving too slowly or too quickly can endanger the quality of insights from Analytics and the adoption success within the organization (Long, 2011).

Figure 3. Based on 857 responses from 179 respondents (4.8 average responses per respondent) (Russom, 2010)

Nevertheless, the research project was mainly aimed to cover abovementioned concerns going around the organizations in order to adopt Analytics at enterprise level. The ramification of the research project endeavored to achieve a consistency on the level of effective Analytics adoption across functional units within an organization. The adoption of Analytics in the Netherlands has appeared to be at the developing stage of initiative creation within certain type of industries. Hence, a better perception on the adoption process was exploited in this study to tackle the common issues emerged in the organizations within the Dutch market.

1.2.2 Research Objective

Once the research context has been explored, unexpected interconnected problems might emerge along the way. In order to demarcate this extensiveness of the research scope, a clear and concise research objective was formulated as follows:

The main purpose of the research project is to design a conceptual Enterprise Analytics adoption model by exploring the Analytics adoption process within organizations.

In order to utterly understand, the main purpose was jotted down into three particular research goals:

A. to examine the adoption of various Analytics applications by organizations in the Netherlands.
B. to investigate the facilitating and inhibiting key factors that affects the adoption process of Analytics.
C. to develop a conceptual adoption model to guide an organization in its transformation towards the competitive Analytics organization.

1.2.3 Research Questions

Based on the main purpose of the research project, and by understanding the problems at issue described on the previous section, a main research question was formulated to bring out a focus for the execution of the research project and to provide guidance during the writing process of this thesis. The main research question was:

How to transform an organization towards an analytical competitor?

In order to provide an accurate answer to abovementioned main question, a set of research sub-questions were developed. These sub-questions were treated as the main topics during the data collection sessions as well as in the discussion of data analysis that are elaborated in Chapter 5 and 6, respectively. The formulation of the sub-questions was as follows:

RQ1. How do organization characteristics differ in the extent of adoption of Enterprise Analytics? What are the key differentiators attached to organizations that have adopted or interested in adopting Analytics in their organizations? *(This sub-question is derived from research purpose A).*

RQ2. Which key factors are essential in facilitating or inhibiting Analytics adoption in medium-to-large enterprises? *(This sub-question is derived from research purpose B and C).*

RQ3. Which adoption phases are accounted to be the most critical phase to endure? *(This sub-question is derived from research purpose B and C).*

RQ4. Does the conceptual design of the Enterprise Analytics adoption model adequately provide consistent approaches and describe the clear adoption process to be able to achieve a new business value offered by Analytics? *(This sub-question is derived from research purpose C).*

After being familiarized with the research context and getting into the conceptualization of the study area, a research design was accounted to be crucial to provide a direction in the execution of the research project. Next section explains how the research design was framed to underpin the scientific research approach.

1.3 Research Design

Throughout this chapter, the research approach and the motivation of chosen methodology are described to form a direction of the research execution. Subsequently, a research framework was built to provide a systematic representation and the guidelines to achieve the research objectives that were defined before. A brief description of data collection instrument employed and correspondingly the analysis tool and techniques applied are given.

1.3.1 Research Methodology

Since there is no simple clarification system to represent a single research methodology applied in a particular research project (Emory & Cooper, 1991; Montero & León, 2007), a number of variations in different research types are covered in this section. Pertinent types of the research design are specified to endeavor coverage in diverse perspectives and to create a clear understanding of the research being performed.

Exploratory Study

An exploratory research represents the nature of this research project. While the researcher lacks of a clear idea on which problems could be encountered in the course of the study, this type has been accounted as an appropriate manner to represent the research (Emory & Cooper, 1991; Sekaran & Bougie, 2009). Exploration in the area of interest was necessary to gain deeper insight to the research context and to provide solutions to the research questions. The rationale behind this selection was based on the fact that the development of the Enterprise Analytics domain has been relatively in an infant stage. Nevertheless, an exploratory research will allow the researcher to gain deep information of the field of study from related stakeholders and experts (Verschuren & Doorewaard, 2010).

Qualitative Research Using Interviews

The method of data collection has been opted to be in the narrative mode, wherein the researcher questions the matters at hand and collects responses from the respondents. Mostly, the purpose of a qualitative interviewing is to derive interpretations from interviewees response, not from facts or laws (Gubrium & Holstein, 2001), as this was also the case here. A semi-structured interview session was held one-on-one with each respondent. A telephone and electronic mails were utilized as data collection instruments. These instruments were used to approach the potential respondents, make appointments with respondents, and communicate relating to the approval of interview results. Further elaboration on the data collection methodology is discussed in Chapter 5.

Field Study

The research project has taken place under actual environmental conditions. The interview session was set up as a fieldwork. Appointments were made with the field experts and the individual interviews were held mostly at the office of the respondents. Visiting the 'field' of respondent's work environment or the client sites was preferable to gain more attention and extensive information from the respondent. Further motivations on selected data collection method can be referred to section 5.2.1.

No Control over Variables

In terms of researcher's ability to manipulate variables, the researcher had no control over the variables when applying an ex post facto design (Emory & Cooper, 1991). No influences from the researcher were allowed in order to avoid any potential biases. The ramification of this research project was therefore relatively merely in terms of reporting what was happened and what is happening by judicious extraction of the analysis, and, to certain extent, by statistical manipulation of findings.

Nevertheless, the research methodology of this study can be mainly characterized by the natural phenomenon of an exploratory study aided by the conformation of field experts through interview sessions. Data gathered has been processed and analyzed qualitatively to be able to provide answers to the research questions.

1.3.2 Research Framework

The focus of the research project has been adopted from Accenture's business operating model, as can be seen in Figure 4. Four organizational elements namely the *process*, *people*, *technology*, and *structure* have been explored to unravel its roles within the adoption of Enterprise Analytics. An operating model was constructed based on the marketplace trends, which were reflected to the corporate's business strategy that targeted its customer, product, route-to-market, and its value. Accordingly the operating model strategy was formulated based on the business strategy. In order to be able to serve its targets efficiently and effectively, the organizational elements are the key enabling factors to gain the business values desired by the organization.

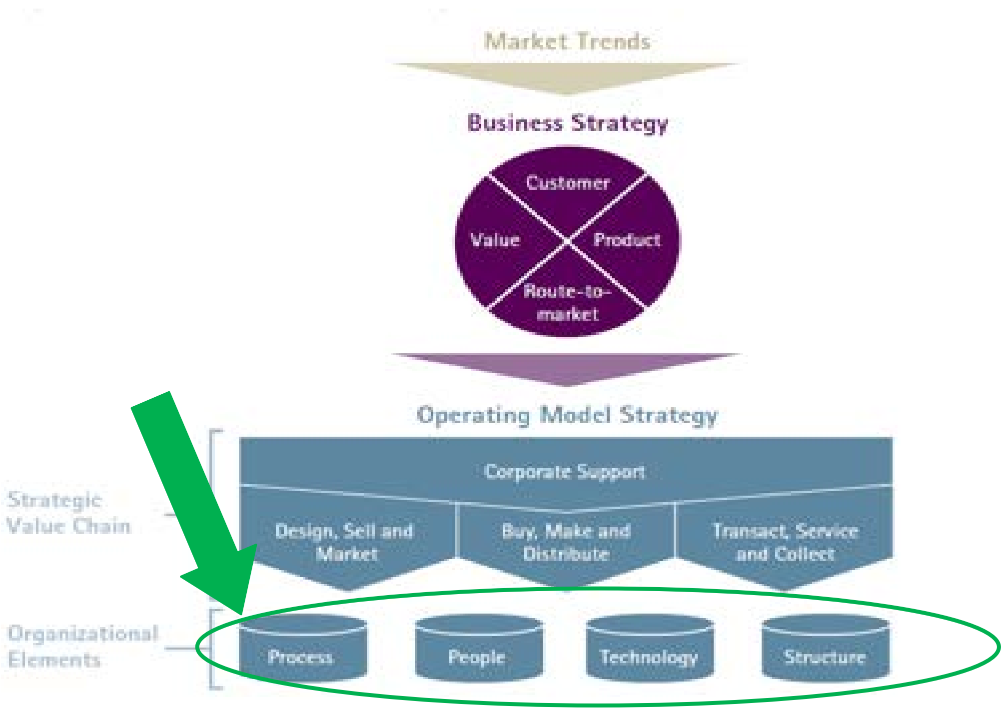

Figure 4. Accenture's Operating Model Framework (Langlinais, Peterson, & Peters, 2008)

Focusing on the organizational elements, a research framework has been constructed to create a clear overview and guidelines to the execution of the research project. The research framework was adapted from the Information System Research Framework (Hevner, March, Park, & Ram, 2004) and presented on the following Figure 5. This research framework has been considered to be properly visualizing the plan of approach to obtain answers to the research questions. An effective problem representation should be selected to find an effective design solution (Weber, 2003). In addition, solving a problem simply means to represent the problem in order to make the solution transparent (Simon, 1996).

The research environment encompasses the four organizational elements as the foci of the study area. These elements were the ones that raise the problem at issue and define the goals, tasks, opportunities and the most important, the business needs. Once the research activities to address the business needs have been framed, the relevance of the research can be assured. The goal of proposing a new model was to facilitate organizations adopting Enterprise Analytics by exploring the common Analytics adoption process at current situation. The conceptual adoption model has been denominated as the ADOPT-model, which was evaluated with the focus on the organizational elements, and refined by the verification of the field experts through a number of interview sessions. Since the conceptual model was constructed based on an applied research environment, it could also be applicable for the practical adoption issues within the organization environment. Nevertheless, the conceptual model contributes also to the body of knowledge within the field of Enterprise Analytics adoption.

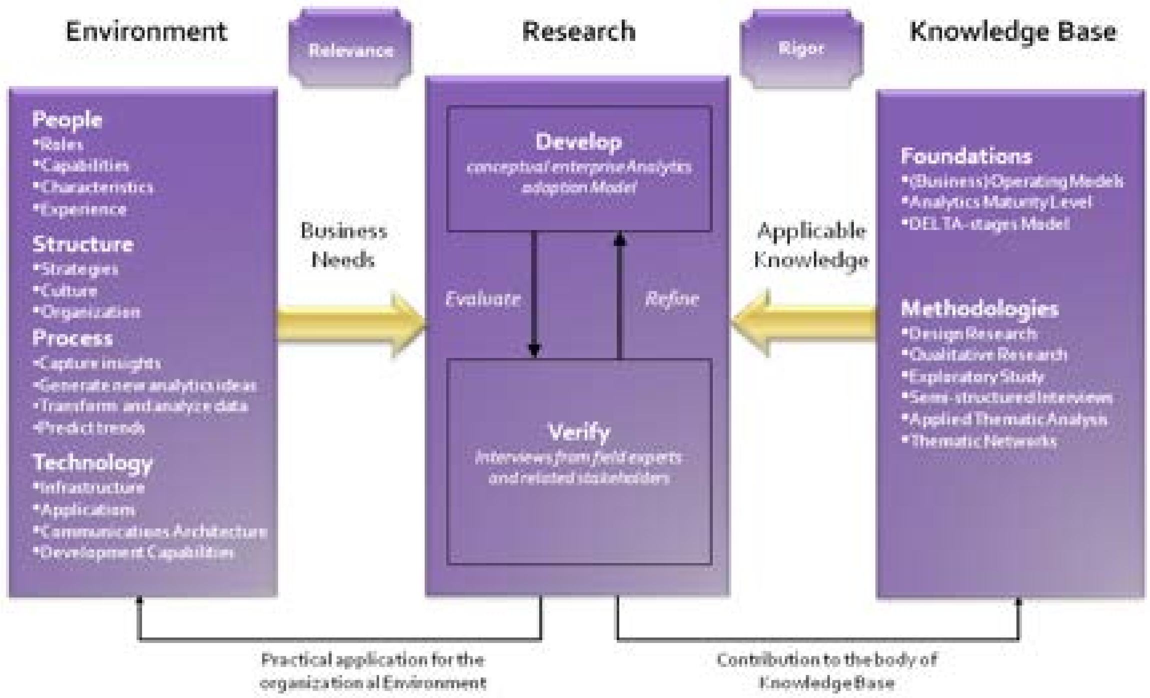

Figure 5. Research framework adapted from (Hevner et al., 2004)

1.3.3 Data Collection Instrument

A research design plans and structures the investigation of the study area in order to seek for the solution to the research questions. The overall scheme of the investigation is structured to obtain the empirical evidence on the relations of the problem as well as the selection of sources and types of information (Emory & Cooper, 1991). As given in the research methodology, the research project has applied a qualitative research approach using interviews. Field experts were selected from both group of consultants and experts from the client-organizations. This group of field experts was questioned thoroughly regarding to the research topic following the interview protocols constructed before the interview sessions. Further exploration of data collection instrument is described in Chapter 5.

1.3.4 Analysis Tool and Technique

As excessive information conceived when collecting primary data, unstructured data was avoided as the data collection can become inextricably intertwined in the most in-depth interviews (Gubrium & Holstein, 2001). Consequently, a qualitative research tool was employed to aid managing and structuring all data gathered. Moreover, Applied Thematic Analysis approach has been opted to process and analyze data gathered from the interview sessions, while thematic networks were generated for the presentation of the analysis result. Chapter 5.6 conceptualizes the Applied Thematic Analysis approach and its relation with the well-known Grounded Theory approach.

1.4 Relevance of the Research

The result of research project comprises relevancies in academic perspective and for practitioners. These relevancies are explained throughout the following paragraphs.

1.4.1 Scientific Relevance of the Research

Besides the managerial relevance, the research contributes to the development of the theory of Analytics adoption model. The ADOPT-model contains a generic nature for organizational transformation in adopting Analytics solution with respect to the business-IT alignment. Due to the novelty of the study area within adoption of Analytics, the conceptual model can be considered as a departure point for customization to be applied in specific purposes. Accordingly these exploratory analyses can be used to generate hypotheses or theories for further study. In this manner, a grounded theoretical model could be developed from the data gathered or research findings resulted from the construction of the conceptual adoption model in this research project. Next interview rounds may be conducted until the saturation of conceived information is reached by the researcher, and subsequently a grounded theory can be generated. In addition, the analysis results of data collected can be used to triangulate other similar research in Analytics adoption domain with the application of different research approach than qualitative research using interviews.

1.4.2 Practical Relevance of the Research

Analytics has shifted from the necessity for a limited group of expertise (e.g. statistician, analyst) to a necessity for a broad group of business professionals to do their job. The availability of various

Analytics applications, e.g. prebuilt or packaged Analytic solution for a specific industry as well as horizontal decision processes, increases the Analytics accessibility to a wider cross-section of organizations. Employees have easier and shorter access to the analysis of information and are able to incorporate this information into everyday work tasks. Decision-making responsibility will be shifted to more individual in an organization that will be also flattening the hierarchies and therefore more timely and effective decisions can be made. The aforementioned value proposition may add value to an organization once Analytics is fully adopted in the organization. Furthermore, the conceptual design of ADOPT-model can be employed to accelerate the transformation of organizations to be competitive Analytics organizations. It prescribes the approach for the entire organization and accordingly creates initiatives and fosters their Analytics capabilities. The construction of ADOPT-model was to facilitate the adoption of Analytics within enterprise-wide by operationalizing pertinent actions to be undertaken.

According to the verified research model, ADOPT-model has the power to explain and foresee a successful adoption of Enterprise Analytics in related businesses. The study therefore contributes a better understanding of benefits regarding the deployment of Analytics applications for the business in Dutch market as the conceptual enterprise Analytics adoption model has empirically tested in the context of wide adoption across different business units in an organization. The model provides also guidance for Dutch business organizations to evaluate their current organization in order to pamper their organizational readiness to be Analytical competitor organization. On the top of it, this model has essential implication for the top management and policy makers to communicate effectively with related stakeholders, in particular within their organization, regarding their Analytics adoption intentions.

1.5 Structure of the Thesis

In order to gain the first view of the remaining of this thesis, a set of research topics is described briefly. The research themes of each chapter are systematically structured in the following paragraphs.

The introduction in the *first chapter* describes the rationale behind the research project that comprises the research problem at hand (why), research main objective and research questions (what), research design (Howitt & Cramer) and who the problem owner was. The relevance of the research is presented in scientific perspective as well as practically. The research scheduling of the entire project is given in the project timeline that can be found in Appendix A. At the end of this chapter, a report structure is systematically structure in a representation of a diagram.

The conceptualization of the Analytics domain is described in *second chapter.* Diversified definitions of the term and possible intertwined understandings between main subjects are explained profoundly in this chapter. Next, the current situation and trends in Analytics are discussed and accordingly any potential opportunities and challenges faced by Analytics are identified to determine plan of approach for the future.

In the *third chapter*, a review of relevant literatures is thoroughly described and evaluated to create a theoretical base for the research activities. Constructing a business model is an approach to capture and to create a new business value for an organization. The ontology, definition and utility of business models are described to put a perspective on how organizations would propose their service value and on how their customers would perceive value from their services. A business operating model is indispensable for an organization to construct their business capabilities to execute its business strategies (Langlinais et al., 2008). In addition, the typology of several operating model from different organizations is presented in the Appendix B.

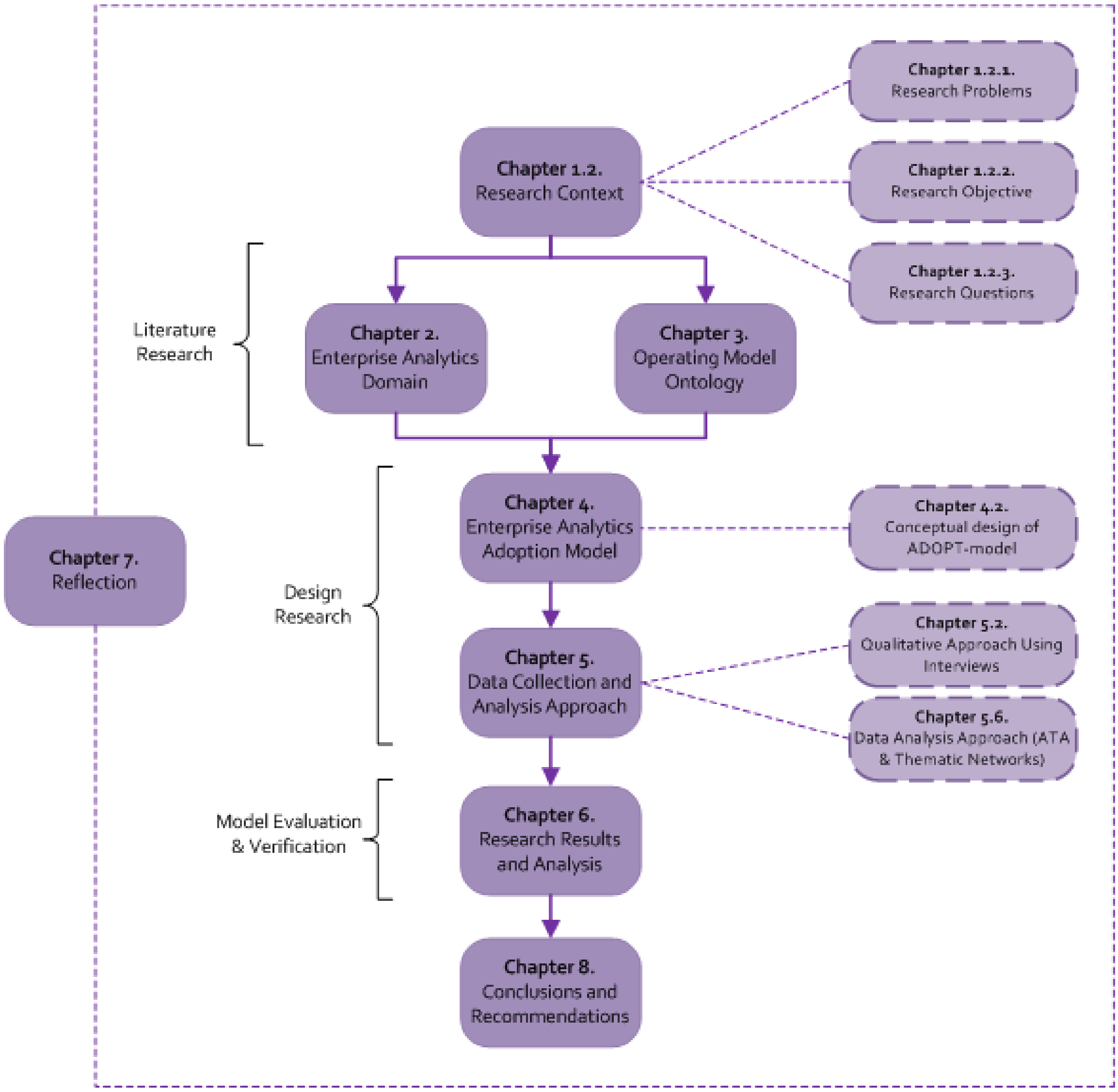

Figure 6. Thesis systematic outline

Chapter four comprises the conceptualization of the Enterprise Analytics adoption model. The initial design of the ADOPT-model has been constructed in prior to the primary data collection, and later was evaluated based on data gathered during the interview sessions. The discussion around the evaluation of the initial design of ADOPT-model can be referred to Chapter 6. Also, the related framework on the maturity level of Analytics is presented in Appendix C that can be used to underpin the development of Enterprise Analytics adoption model.

Data collection methodology and rationale behind chosen methodology are discussed at the beginning of *chapter five.* Accordingly, data collection protocols with corresponding selection criteria for respondents are described to prescript the line of actions to obtain reliable data. Moreover, the explanation of data analysis approach is given as well in this chapter.

Once all data gathered, the data analysis and result will be presented in *chapter six* and followed by the discussion of verified ADOPT-model.

After the results of data analysis are presented, these research findings will be reflected back starting over from the initial purpose to conduct this research project. The reflection in *chapter seven* is concerning the conceptual ADOPT-model, the reliability and validity of the research findings and model verification, as well as the entire research process.

This thesis ends the research reporting with *chapter eight,* which comprises the main research findings by answering the research questions formulated in the first chapter. The critical success criteria in adopting Analytics are conveyed to the practitioners to be regarded as the recommendation based on this research findings. Finally, the research limitations and direction for further research are described to be taken into account by the successive researcher regarding this research theme.

Chapter 2
ENTERPRISE ANALYTICS DOMAIN

"Most people use statistics the way a drunkard uses a lamp post, more for support than illumination."
~Mark Twain

2.1 Introduction

The conceptualization of Enterprise Analytics domain is covered in this chapter. Firstly, the discussion about what the precise definition of Analytics is and its intertwined definition with Business Intelligence are conveyed in Chapter 2.2. A brief history of the emergence of Analytics semantic and several types of Analytics are explained in Chapter 2.3. Subsequently, Chapter 2.4 depicts how today's market and trends of Analytics look like, and followed by the exploration of potential opportunities and challenges entailed from adopting Analytics within organization.

2.2 What is Analytics?

Diverse definitions are attached to the term of Analytics based on different people's perspective and business needs. Unfortunately, there exists no exact the same meaning that was accepted by everyone and neither was found in the literatures. According to Davenport and Harris (2007), the most common used term of Analytics today can be defined as "*the extensive use of data, statistical and quantitative analysis, exploratory and predictive models, and fact-based management to drive decisions and actions*". In the sense of a group of tools, rather than the technology in and of itself, the term simply means of applying various advanced analytic techniques and combines them to obtain and analyze the information, and predict the outcomes to solve problems (Bose, 2009). Similarly to this, Laursen and Thorlund (2010) have considered Business Analytics not merely as technical solutions but as Information Systems that is constituted from three elements, i.e. technological element, human competencies, and some specific business processes that need to be supported. Some studies describe Analytics still as part of the Business Intelligence (BI) in which many of analytical techniques are used in BI reporting, ad-hoc queries and real-time analysis (Bose, 2009; Burstein, Holsapple, Negash, & Gray, 2008), while others define Analytics as nothing else but the new BI semantic with more advanced discipline beyond traditional BI reporting and analysis tools (Laursen & Thorlund, 2010).

As well as Analytics, the term of BI can be explained in different viewpoints. According to Adelman *et al.* (2002), "*Business Intelligence is a term that encompasses a broad range of analytical software and solutions for gathering, consolidating, analyzing and providing access to information in a way that is supposed to let an enterprise's users make better business decisions"*. In a more strategic point of view, the term was defined by Rouibah and Ould-ali (2002) as a strategic approach to target, track, communicate, and transform fragile signals systematically into actionable information on which strategic decision making is based. Malhotra (2000) has pointed out the benefit of BI that facilitates the connections in an organization, whereas real-time information is brought to centralized repositories for supporting Analytics. This information can be exploited at every vertical and horizontal level within and outside organization. Moreover, BI is defined as the result of in-depth analysis of detailed business data, including database and application technologies, as well as analysis practices (Gangadharan & Swami, 2004). Other studies describe BI as much broader technical tools, which include several software's for extraction, transformation and loading (ETL), data warehousing, database query and reporting, multidimensional/online analytical processing (OLAP), data mining, and visualization (Berson, Smith, & Thearling, 2002; Sahay & Ranjan, 2008). Other BI concepts have defined the understanding according to different fields of experts. For Customer Relationship Management (CRM) experts, BI is the integration between operational front-office applications and operational back-office applications where both applications are strongly interrelated. To some data warehouse experts, BI is merely a new term that provides decision support on a new technology platform. And to some data mining statisticians, BI still represent data mining algorithms but more advanced ones (Gangadharan & Swami, 2004).

'Analytics' or 'analytics'?

Hitherto, some means and others have intertwined the definition of what exactly Analytics and BI are, and its correlation with data warehousing, data mining, decision support system etc. However, to certain extent the purpose of both Analytics and Business Intelligence can be defined as to help organizations exploit business data to generate 'smart' decisions or to make a more data-driven business decision despite any technologies, techniques, or system infrastructures used. For the sake of simplicity and clarity, two distinctive dimensions of Analytics have been assigned in this thesis to reflect whether to its industry context or its technology context. Analytics with capital letter "A" refers to an umbrella term representing the processes where data turns into information and knowledge to support decision-making in business environment. While analytics with a small "a" refers to a variety of tools or techniques that are used to analyze data, e.g. Excel, OLAP, machine learning model, statistical modeling, optimization tools, etc.

2.3 Emergence of Analytics

According to Eckerson (2011), there has been an evolution of terms accounted to the denotation in the business reporting and analysis domain. Business experts with new theories and vendors with new technologies have induced a novel term to revitalize their ideas, products, and fields (Eckerson, 2011b). A wave of trends and expectations have emerged from each new term, whereas some discontents of the adoption in the long run might urge people to come up with another innovative terms. The chronological order until Analytics became a far-flung known term for business optimization in enterprises is described in the following paragraphs.

In 1960s – 1980s: Decision Support

Many BI experts have believed that the term of Analytics was rooted from *Decision Support System (DSS)* (Burstein et al., 2008; Davenport & Harris, 2007; Eckerson, 2011b). The concept of interactive computer-based systems that was used to analyze data and support decision-making arose as early as the late 1960s. Later in the late of 1970s, a number of companies had used data and models in interactive information systems for managers to analyze ill-structured problems. From 1980s, DSS was acknowledged as the support tool in helping decision teams and individual decision makers to improve business processes widely in diverse business transaction, financial management, and strategic decision-making. Sometimes it was referred to vertical-market or industry-specific DSS (Power & Sharda, 2009).

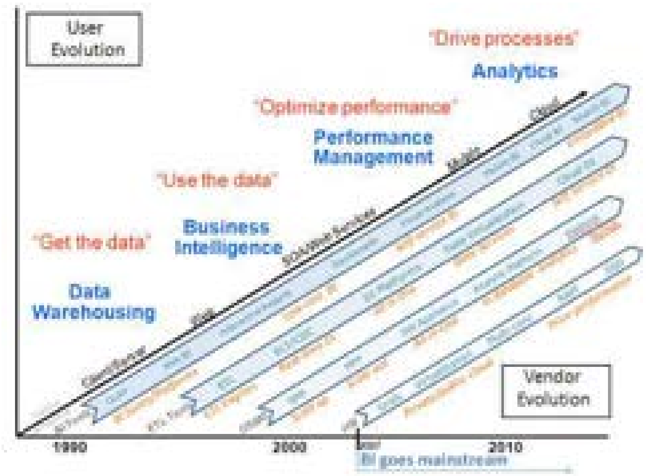

Figure 7. Evolution in BI semantic (Eckerson, 2011b)

Later DSS technologies were designed to be targeted at senior management and it evolved to focus more in ad-hoc decision analysis for specific purposes, also often in real-time. This system was called as *Executive Information System (Blenkhorn & Fleisher)*. Further, another demand for IS has evoked to target professional and managerial activities in creating, gathering, organizing, and disseminating knowledge within an organization, as opposed to "data" or "information". This refers to *Knowledge Management Systems (KMS).*

The contribution of aforementioned three systems was recognized in the improvement of individual and organizational decision-making ability. This will continue to be the important component of organization's Information Technology. Traditional DSS has become firmly established in the main stream of IS practices and employing decision-making applications has become a common practice to solve problems in present business challenges in a more timely and easily consumed way (Elam, Huber, & Hurt, 1986).

In 1990s: Data Warehousing

As huge backlogs of requests periodically recorded in tapes has been solved in the past due to *distributed database management system (DDBMS)*, accessing data directly from the transactional database with "islands of data" was still a problem. Real computer applications were decentralized and need a new solution to optimize and manipulate data. Earlier in the late 80s, Devlin and Murphy (1988) as first had described the data warehouse architecture and published in the *IBM Systems Journal* (Devlin, 2010). In the early 1990s, IT professionals used a new approach to report and analysis data called "*data warehousing*". They focused on gathering and extracting data out of operational systems, and put into an optimized database regardless the number of different applications or platforms. After undergoing a heavy construction of building a DW, organizations realized that there was still no guarantee that business people would take a use of it.

In 2000s: Business Intelligence

The term was actually used for the first time in 1989 by Howard Dressner, one of the researchers at Gartner Group (Burstein et al., 2008). He has described *Business Intelligence (BI)* as the umbrella term of concepts and methods to improve decision-making by fact-based support. However, early in the 2000s IT professionals began to focus in the usage of DW for Web-based reporting and analysis tools to be more user-friendly for business community, and make the business itself more intelligent. Ever since, the term "Business Intelligence" became the business-IT industry's catchy word. Unlike the previously mentioned decision support systems that have characteristics as limited database, modeling, and user interface functionality, BI systems are data-driven decision support system (Power, 2007). BI can be applied in many areas related to enterprise management processes whereas some BI systems have been formed with specific characteristics (Holsapple & Sena, 2003). Many BI applications related to the area of customer relationship management (CRM), supply chain management (SCM) or human resources management (HRM). However, getting the business users to easily employ BI tools did not happen promptly. BI became cumbersome for business reporting and analysis tools and often became expensive shelf-ware.

In 2005 – 2010: Performance Management

The Business-IT industry attempted to bestow a new semantic upstart that focused on business outcomes. The term "Performance Management" was called out to blow away the business executives with the outperforming performance of dashboards, balance scorecards, and planning tools that align the organization's business strategy with IT objectives and optimize the performance at all levels of the organizations. Soon the executives recognized troublesome in defining metrics and targets in Key Performance Indicators (KPIs) that was often subject to the sequences of politics and bureaucracy as in the top-down approach.

In 2010+: Analytics

Many authors from academic and practical literatures have acknowledged the preeminence of the term "Analytics" gained from business executives since Tom Davenport and Jeanne Harris have released their influential book titled "Competing on Analytics" in 2007 (Eckerson, 2011b; Lustig, Dietrich, Johnson, & Dziekan, 2010). Another distinctive competition advantages were sought by organizations that emphasize the agility in leveraging information to make smarter decisions. Analytics was initially referred to advance statistical modeling with help of analysis tools such as SPSS and SAS. Later Analytics has been considered as an advance discipline within BI that heavily associated with technical solution that goes beyond the traditional BI reporting and analysis for end users in the frontier creation of sustainable competitive advantage (Laursen & Thorlund, 2010).

The evolution of term Analytics is visualized in Figure 7 starting from the year 1990 as the early adopter phase known as data warehousing to the early main stream as in BI market (Eckerson, 2011a). Different computing platforms where BI technologies are running on have been identified as well. The compute infrastructure has evolved in dramatic change over the years, from mainframes and mini-computers in 1980s and client/service infrastructure in 1990s, to Web and Web services in the early 2000s. The proliferation of mobile and cloud computing appears everywhere these days. As the BI market has been proved to be changed and innovating its technologies, products and methodologies to be a better self-service BI tools such as the use of mobile and cloud services, the emergence of Analytics opens a new opportunity in leveraging added value to organizations to survive in this changing market conditions.

2.3.1 Types of Analytics

Eckerson has described different types of Analytics as the followers of a wave in company reporting (Eckerson, 2011a). The first wave of Analytics addresses the question "*Why did it happen?*" and it is *deductive* in nature, while the second wave addresses the question "*What will happen*" with primarily *inductive* nature.

In *deductive Analytics*, business users formulate the hypothesis as a root cause of a deviancy or performance alert, to be explored using analytical tools. If the hypothesis is falsified then a new formulation of hypothesis for further data exploration must be searched. A term of Data Warehousing is often used here, which refers to analytical databases and ETL tools. Oppositely, in *inductive Analytics* the business users have to start with a business outcome of goal formulation. They used analytical tools to discover patterns or to create statistical or machine learning models of the data to answer their questions to achieve their goal. A prediction is produced by statistical modeling or by data mining, and optimization is possible to make. The company reporting and query tools comprehend a "*What happened?*" - question which also known as Business Intelligence. Other tools such as dashboard, scorecard, and planning tools relate to the Performance Management that can answer the *"What is happening?"* - question as to monitor within business processes.

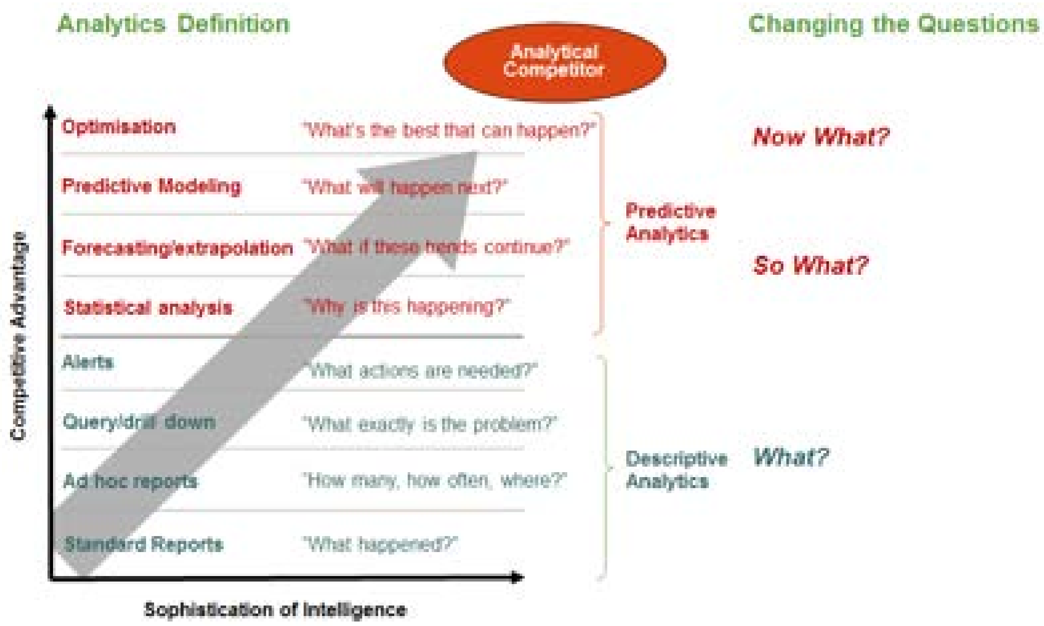

Figure 8. The more sophisticated intelligence of an organization, the greater competitive edges can be reached (Davenport & Harris, 2007).

The IBM, one of big Analytics vendors, has proposed another view in categorizing Analytics. They enhanced the definition of Analytics as "*the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and actions*," from Davenport and Harris in their book "*Competing on Analytics: The New Science of*

Winning" (Davenport & Harris, 2007). Instead of having a certain definition of the meaning of Analytics, Lustig et al. (2010) have distinguished the analysis of (un)structured data in threefold:

2.3.1.1 Descriptive Analytics

The representation of a set of data used is to understand and analyze business performance of the pass as well as real-time events. This type recognizes three areas of analytical techniques that answer particular kinds of questions:

- *standard reporting and dashboards* (e.g. budget, sales, revenue and costs): What happened? What is happening now? How does it compare to our plan?
- *ad-hoc reporting*: How often does a certain event occur? How many? Where?
- *analysis/query/drill-down*: Why is it happening? What exactly is the problem?

Descriptive Analytics provides significant insight into business performance, and enables business users to better monitor and manage business processes. However, it relies only on the human ability to review a vast of data to generate insights into what is happening now or has happened in the past. Robust techniques to facilitate the understanding to what might happen in the future, or the tools to suggest decisions on what should be done next, are not incorporated in this type of Analytics. Typical organizations that can effectively employ descriptive Analytics have a single view, rather than different views, on how they look the past and focus their attention on the present. Additionally, this type is often considered to be the initial step to serve a successful application for predictive or prescriptive Analytics.

2.3.1.2 Predictive Analytics

This type of Analytics can be described closely to Davenport and Harris's idea as an extensive use of data and statistical techniques to uncover explanatory and predictive models of business performance. These models inherit relationships between data inputs and outputs/outcomes. Predictive Analytics applies various *advanced techniques* to make "predictions" about the future based on the understanding of the past. It utilizes techniques that segment or group amount of data into coherent sets such as *clustering*, *decision trees*, and *neural networks.* Most techniques used are:

- *data mining*; activities such as examining scenarios in time series, evaluating past data and trends in order to predict future demands (level, trend, seasonality), can be used as a guide to answer questions such as: "*Which customers are most likely to purchase our product?", "Which patients are most likely to respond to a given treatment?"*
- *pattern recognition and alerts*; patterns are extracted from a quantity of data to predict non-linear behavior that can be used to decide on actions will be taken in the future, for example to recognize suspicious insurance application transaction which the future claims can be flagged as a possible fraudulent that need to further investigate.
- *Monte-Carlo simulation*; by exercising an algorithm model or mathematical constructs under various scenarios, a prediction or estimation of future behavior will be known prior to the real event with high probability of occurring.
- *forecasting*; this is most applied technique used in business processes that is not only predicting the workload but also including enterprise planning such as human resources required to carry out forecasted activities into a desired end state. Together with the final

milestones for compliance activities agreed upon operational plan refers to *performance management system*.

- *root cause analysis*; try to find an answer to *"Why did something happen?"* – question.
- *predictive modeling*; similar to other advanced analytics techniques to provide information what will happen next if something happens.

The real-time operational processes are aimed to be affected in activities such as real-time identification of suspicious transactions from insurance companies, or customer retention via chat messages. Other predictions are also made to target new customers on Web sites, to direct mail to drive cross-sell / up-sell or to recognize patterns or relationships that can be extrapolated forward in time. Data from descriptive Analytics (i.e. descriptive data such as demographics or characteristics of individuals) is combined with behavior data (transaction, payment-, orders history), interaction data (chat transcript, e-mail), and attitudinal data (preferences, opinions) to obtain a complete view in predictive Analytics. Putting together the static view of the past from descriptive Analytics in repetitive way of evaluation, classification, and categorization by fast algorithms, a measure of adaptability can be reached. If this stage where anticipatory actions are supported then a threshold into the predictive Analytics is crossed over.

2.3.1.3 Prescriptive Analytics

The most enhanced type of Analytics is prescriptive Analytics where business users are enabled to deploy real-time actionable decisions in facing a wide range of business problems. It comprises a set of mathematical techniques that computationally generates robust alternative actions or decisions within given requirements, objectives, and constraints. Thus, not only predicting but also providing high-value decisions for actions to improve business performance is the goal of this type of Analytics. It covers the area where the best response or actions are crucial to solve business problems within given circumstances or limited resources of the organizations. The analytics techniques used here are based on the concept of optimization, which is classified into two domains:

- *optimization;* how to achieve the best outcomes?
- *stochastic optimization*; finding the best way to achieve best outcomes and addressing uncertainty in data in a way that risks of an action can be mitigated and therefore better decisions can be made to maximize business performance.

Mathematical optimization plays an essential role in modeling a system that produces potential decisions. This optimization is applied in many industries ranging from operational scheduling to the long-term planning to meet their constraints and requirements. Additionally, analytical techniques in predictive Analytics can be combined with optimization, which is called stochastic optimization where uncertainty is taken into account and high-volume transactional applications are not applicable.

The classification of *descriptive Analytics* can be considered as diverse applications in Business Intelligence. The term of "*Advanced Analytics*" refers to the *predictive* and *prescriptive Analytics*, where the analytical techniques applied are accounted to be the comprehensive mathematical algorithms and are beyond the techniques used in Business Intelligence. Comparable to this, Davenport and Harris (2007) have categorized prescriptive Analytics as predictive Analytics where *optimization* is still considered as predictive intelligence.

2.4 Analytics Market and Trends

2.4.1 Global Economic Shift

The global competition has become more intensified ever since the economic crisis hit worldwide in 2008. According to Fortune Global 500, the number of growth companies in United States has dropped from 176 in 2005 to 133 in 2011. In contrary, the number of growth companies in China has increased from 16 to 61 companies in corresponding years (CNNMoney, 2011). None of the Asian countries was included in the Global 500 listed back in 1997, except for Japan. The emerging countries dominate almost exclusively the global economic growth, where emerging markets account for around half of economic output worldwide with the largest contribution from China. The Economist (2012) has forecasted China's contribution during 2010-2013 to be 31% on average compared to 8% in the 1980s (Economist, 2012). The International Monetary Fund (IMF) has expected the emerging countries to contribute over 80% of world GDP growth in 2012. After being dragged down by the Euro crisis, the advanced countries are not anymore leading the world economic growth. However, the world has showed a recovery returning to the growth in 2010 (see Figure 9) but each country is recovering at different paces.

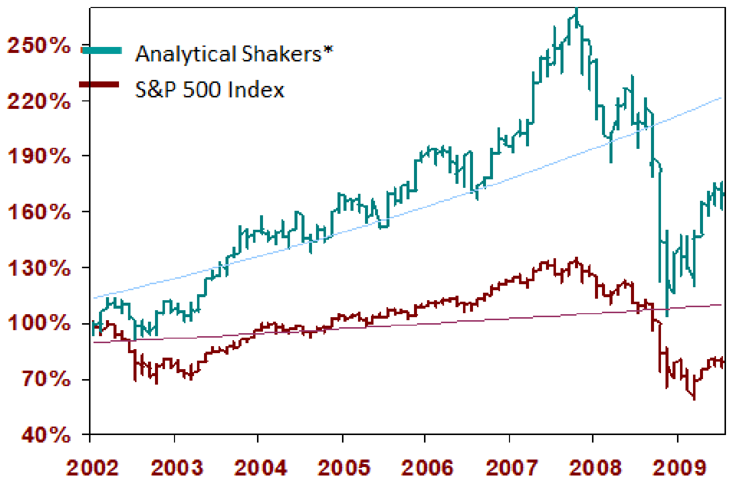

Figure 9. Market performance of Analytical companies compared to S&P 500 index

Figure 10. World GDP growth rate (Economist, 2012)

High unemployment strikes the changes in customer behaviors and demands on products or services offered by companies. The customers' dynamic behavior enforces business activities to adapt on their volatility and to innovate further in order to be able outliving the recession. New trends require organizations to leverage more sophisticated technology advancement. Rapid and better decisions are the keywords in operating business within increasing market and competitive volatility since there will be a greater emphasis on data innovation and a dramatic shift towards the consumption layer (Accenture, 2012). Data explosion (internal- and external data) is considered as a key source for the insights in competitive and commercial markets. The graphic in Figure 10 has showed the out-performance of companies that invest heavily in developing analytical capabilities and adopting analytical mindset, towards the S&P 500 (the common stock prices based on 500 American companies) on average by 64%. They tend to recover quicker from economic downturns as well (Accenture, 2012). Analytics is expected to be embedded in business applications that accounts for 25% by 2015 compared to 5% in 2011, and Analytics insights will be consumed on mobile devices with a rise to 33%, as well as the use of Analytics applications for collaboration and social software integration with 15% by 2013 (Accenture, 2012).

2.4.2 Need for Analytics and Data-Driven Decision Making

Many large, once-booming, companies have failed to preserve their existence in complex business environment from recent years. Some have been reduced substantially in size, others have fallen from their position as industry leader, or even have gone bankrupt (Cokins, 2012). Important lessons can be learned from the following brief business case studies.

Box 2.1. *Wang Labs* failed in part due to its specialization in computers designed exclusively for word processing, and did not foresee the general-purpose of Personal Computers (PCs) with word processing software mainly developed by IBM in year 1980s. Wang's word-processing terminals were connected with its minicomputers. Eventually Wang's minicomputers were edged out by PCs for many purposes, especially for word processing. As Wang disregarded it and entered the market with computerized image processing at its infancy stage, Wang did not succeed taking over the market share. [1]

Box 2.2. *Digital Equipment Corporation (DEC)* held a dominance position in the core minicomputer market; however, it was slow to adapt its product line to the new markets for Personal Computers (PCs). Many senior managers and engineers saw the market shift away from minicomputers to PCs around 1990's and acknowledged the need to react on it, but unfortunately DEC could never make the trade-offs to be more competitive. Technical-oriented culture has embedded prominently through organizational set of values and beliefs that created an immune system to any business solutions from commercial perspective. This brings a subtle lesson for any companies with strong technology-oriented DNA to realize the need for responding to the fast-changing market that would require more cost control, different form of manufacturing, or cutting off certain innovative projects.[2]

[1] Retrieved from *http://community.seattletimes.nwsource.com/archive/?date=19920823&slug=1508984*
[2] Retrieved from *http://markettorrent.com/topic/9477*

Box 2.3. *Blockbusters* was once the most successful movie rental company in the marketplace. It provides rental services of home video and video games through traditional physical stores since 1985. Despite their great success, it has not adapted to the changing business environment and failed to be more responsive to market trends and customer feedback. When the popularity of streaming movie started to elevate, Netflix entered the market with totally different business model and outpaced Blockbusters. Once data is available, actions need to take to collect the data, track, and respond to market trends to secure company's competitive edge, as well as, to stay ahead in the competition of resilient market.[3]

Box 2.4. *Borders* was liquidated in 2011 after the retailer opened his first bookstore 41 years ago in Ann Arbor, Michigan, United States. Borders built a reputation on offering a wide variety books and pioneered the megastore book business. At that time, Borders had a superior inventory system that could optimize and even predict customers' preferences on books they would buy. However, Border's demise was due to some critical missteps over the year. The decision to outsource internet sales chain to Amazon.com, over-reliance on their brand image with huge assortment size, and over-investment on Border's music business played essential role in Border's failure.[4]

The business case studies demonstrate what happens when a once-successful company neglected fundamental changes in its dynamic market industry. Why did they fail to maintain their market position? What caused their failures? Were they not analytical enough in their decision-making processes? Even though they had superior technology at that time, in particular Borders with its inventory system that can optimize and predict customer behavior, but still made faulty decisions. As most economists believe that human rationality is bounded, there are limits to the reasoning abilities of human being as information processors (Arthur, 1991). Bounded rationality has been characterized by largely failures of knowing the alternatives, uncertainty about relevant exogenous events, and being unable to calculate consequences (Simon, 1979). Due to this limitation, are human beings enforced to rely only on their intuition or heuristics approach in solving problems? Although many organizations today are still operating their businesses based on "gut feelings" to make decisions, in particular by senior managers, they find it rarely work in current business environment (Kumar, 2010). Problems get more complex in continuous changing economic situation, supplies and demands are unpredictable, and customers today are most empowered than ever. Decisions merely based on intuition without proper rationale seem to have serious implication in the long-term condition of an organization. Various organizations need to step up and take actions in meeting their business needs to be agile organizations that always face a resilient economic environment.

2.4.3 Analytics as a Path to Better Decisions

Due to the resilient and unpredictable environment in today's situation, organizations are compelled to own their strategic, operational, and tactical agility. Organizations need to absorb a new situation quickly and to respond with maximum vigilance of effort at the point of need. Decision-making, also referred to as problem solving, can be considered as the chosen alternative based on certain criteria

[3] Retrieved from *http://www.usanfranonline.com/blockbusters-business-process-management-failure/*
[4] Retrieved from *http://www.npr.org/2011/07/19/138514209/why-borders-failed-while-barnes-and-noble-survived*

or some basis among other available alternatives. Decisions need to be taken based on multiple criteria rather than a single criterion, and often involve multiple actors (Bhushan & Rai, 2004). Decisions made in a semi-structured, unstructured, or ad-hoc manner, or based on partial availability of relevant resources have high likelihood not just to be non-optimal decisions, but utterly wrong, that lead to disastrous results.

Strategic decisions affect the long-term direction of the entire organization and typically made by the top-level management. Such decisions are often complex and the outcomes uncertain due to limited available information. Also, usually made or revised infrequently. This type of decisions can be related to the creation of new policy in focusing effort in new production, or increasing product output, service or an initiative that result in guidelines within which operational decisions are taken.

The realization of corporate strategy goals is pursued a step closer by determining *tactical decisions*. These decisions are repeated frequently and can occur in high volume. The focus of this type of decision-making is more on intermediate-term issues such as an advertising agency selection to market a new product.

For specific project or process in day-to-day activities, the employee or lower-level managers make *operational decisions*. Corporate strategy is translated into guidelines for action as these guidelines are applied to a variety of decision points where actions are taken. Decision made in lower-level management help to ensure daily activities to proceed smoothly and help an organization to move towards its strategic goals. For example planning and scheduling employees, purchasing raw materials, and determining an optimal price.

A virtuous cycle occurs between these decision types to drive continuous improvement. Tactical decisions are monitored with ongoing reviews and adjustments to action guidelines. In turn, the record of these changes becomes an input into future strategy reviews.

As previously explained in Chapter 1.2, top performer organizations prefer five times more for analytical decision-making approach than intuitively, conformed to MIT & IBM research study (LaValle et al., 2010). Analytic insights that serve a strategic decision-making provide corporate executives with necessary information that they will generally review the information and decide on their future vision. Unlikely at the operational level, the value of defined business strategies will not be realized until these strategies are implemented at the operational level (Porter, 2006). Going in more detail, operational decisions are the actions taken for example in transactions and in interactions with customers (Taylor, 2011). By applying Analytics to gain insight in which actions do customer value most, the organization is able to treat its customers more in personalized way so they can reflect back the value they personally have. This way customer’s satisfaction can be increased and higher possibility for customer retention and up/cross-selling.

Many insurance organizations, for instance, have extended their strategic control over underwriting decisions by using Analytics insights. They have increased the efficiency of the underwriting systems for agents and enabled staff to focus less on helping agents to complete transactions but more on improving business and channel productivity. A clear separation is defined between executive level, where analytics insights guide business strategy, and the operational level, where analytics insights help the strategy to be realized in day-to-day business activities (Taylor, 2011).

Figure 11. Better decisions and improved outcomes powered by Analytics (Accenture, 2012)

Improving the business agility brings along more added value to many organizations above their prior defined competitive strategy (see Figure 11). Analytics enables informed decision making in higher speed to be translated in both actions and measurable outcomes that drive high performance (Accenture, 2012; Davenport, Harris, & Morison, 2010; Morris, 2010).

2.4.4 Trends

The use of spreadsheets is the most popular alternative tool of analytical budgeting and planning (Morris, 2010). While a spreadsheet can be productive at individual level, but does not support multiple individuals to collaborate during coordination process. Analytic applications were initially aimed for horizontal processes as department specific that applied equally across industries. Later, the use of analytical application involves multiple users across diverse functional level that was required by today's business needs.

A research conducted in 2007 at TDWI showed that five out of the top seven applications for advanced analytics originated from the *marketing* department. These include analytical works applied in (with descending order) cross sell/ upsell, campaign management, customer acquisition, attrition/churn/ retention, and promotions. Subsequent mostly applied is in *financial* department where budgeting and forecasting, and pricing are calculated (Eckerson, 2011a).

Slightly different, a researcher at International Data Corporation stipulated *financial analytics* that serve cost-profitability analysis, business planning and consolidation was the most common target for analytical applications (Morris, 2010). Financial planning which originates in finance is a good example where the users are spread across the organization. An application for this use requires a collaborative process and the integration from multiple data sources. A consistency in process execution must be preserved and the information should be gathered and consolidated transparently.

Next most common area where analytical applications are used is in the area of *planning*. Manufacturers require the Sales and Operations planning to balance their inventory, capacity, and demand of their products/ services. Scheduling workforce can be tailored to meet many industry-specific needs. Other analytic applications must be able to accommodate some tactical decisions such as supporting near-real-time alteration to key business variables, or some longer-term views such as evaluating the cost and benefits of building new manufacturing plants or healthcare facilities.

Analytics market moved from abovementioned standalone function-specific applications to *applications suites*. Likewise, the application suites focus on a group of users in specific area with related decisions e.g. operational planning, customer segmentation, fraud, risk and control, etc. These suites leverage a common data set that is used across functional units within an organization such as the customer data set.

2.5 Opportunities and Challenges

As many experts believe that, by applying Analytics to drive a business can create new opportunities for organization to build up their new competitive edge (Davenport & Harris, 2007; Eckerson, 2011a; Laursen & Thorlund, 2010), it also entails few challenges that impact the deployment of Analytics across an organization. Successful business Analytics initiatives are typically closely interlinked with the organization's strategy (mission, vision, goals) and are put in place to strengthen the ability of business processes to meet organization's business objectives (Laursen & Thorlund, 2010). Next paragraph describes the new opportunities for organizations that are worth to be captured in business Analytics environment. Subsequently, typical challenges emerged during Analytics adoption will be discussed to create awareness for practitioners before taking further steps reasonably.

2.5.1 Opportunities

Creating analytical models, crunching numbers, and applying statistical techniques and algorithms belong to the heart of advanced Analytics (predictive- and prescriptive Analytics). Using these as data analysis resources can let organizations to better manage their information that drives their decision-making processes, and add values in business processes. According to Gartner (Herschel, 2007), higher business performance can be achieved in these areas:

Better customer insights

Customer behavior and -perception are the main target for data gathering, this can be collected through various social media (e.g. Twitter, Facebook, YouTube), news, report, Web, etc. The social media is a direct tool and has a leading indicator of customer perception that made this imperative to listen to and react. Traditional sources such as sales data lack indicators of performance and might lack of timely action. A brand image can also be managed through customer perception influence, key word associations understanding, and user sensitivities understanding. Better insights in customer data can predict churn, target the most profitable segments, retain loyal customers, index and enhance satisfaction, and increase cross-/up-sells.

Faster product innovation

Analytics typically uses common data across organization. By getting better insights from customer data, customer needs can be tracked on time and be correlated to R&D and service data. Market gaps and new market opportunities, and a potential cross-selling can be identified immediately.

Optimized supply chains

Unnecessary steps in the entire process chain that add cost and time, but add little value can be cut out so an organization can save time and reduce cost. Likewise in refining inventory procurement, sourcing, asset and warehouse management. Market demand forecast can be improved and planning efficiency can be increased. Finally, optimal pricing should be better identified that can meet market purchase power.

Agile financial performance

Despite the fast-changing economic environment, market opportunities and risks can be captured promptly through market analytics. For investors, financial performance knowledge need to be translated into increased revenue, and next potential investments, efforts and pricing changes should be correlated with organization's Return of Investment (ROI).

From an industry-specific perspective, advanced Analytics covers different scope of analysis and typically can be classified as in the following table:

Type of industry	Insurance	Banking	Pharmaceutical	Retail
Scope of analysis	▪ Fraud detection ▪ Underwriting ▪ Direct marketing ▪ Customer cross-sell/ up-sell	▪ Customer relationship management ▪ Customer segmentation ▪ Credit scoring	▪ Drug discovery and development ▪ Clinical data integration ▪ Clinical decision support systems	▪ Supply chain management ▪ Inventory management ▪ Sales forecasting

Figure 12. Analytics' scope of analysis regarding different types of industry

2.5.2 Challenges

Getting Analytics in place across enterprise entails a major alteration in certain layers of an organization. Most typical challenges emerged in organizations that have adopted Analytics can be grouped as in focusing on data issues, addressing expertise issues, and recognizing cultural issues.

Data issues

The International Data Corporation stipulated that data issues cause the most failures of an analytics project, based on their research result that has shown consistently 70%-80% of the effort of an analytics project depends on resolving data issues (Morris, 2010). Right data need to be captured and structured before useful insights can be extracted out of those data. The ownership of data needs to be taken by the business stakeholders so they can create a "common global language" that can be understood by users across the organization when analyzing performance-related topics. This commitment must be engaged before certain type of data can be saved for analysis purposes, and an IT department provides the technical data architecture to support this mandate.

Expertise issues

Adopting Analytics requires many types of analytical skills such as data integration, forecasting, modelling, and simulation to explore patterns and new trends. Organizations often have these skills in house, however uneven distributed at each business unit. To make better decisions, the mathematical modelling and analytics need to be adaptive and flexible. They need to have self-learning capabilities to get increasingly smarter (Cokins, 2012). Hence, the ability to transfer knowledge and learning skill across an organization is the key to success in applying Analytics. Proper data governance and training in analytical techniques are necessary for organizations to provide when they address this issue.

Cultural issues

Organizations differ in their cultures in terms of the way how they support their fact-based decision making. This analytical orientation must grow and decision making need to be data driven to succeed in Analytics. According to an Accenture research, 40% of decisions are still made based on intuition instead of fact-based (Accenture, 2012). Further according to Bloomberg Businessweek Research Services study, the mix of intuition-driven to data-driven in decision-making is 53/47 for those organizations using analytics effectively, and 62/38 for all others (Bloomberg & SAS, 2012). Significantly different from Accenture research, the ratio between intuition and analytics to drive decisions was 60/40 for the survey respondents. However, the actual results seem to indicate that data analysis still cannot fully replace the insights gained through respondent's personal knowledge and experience, even though their organizations realize that analytics can provide insights to make effective decisions. This study involved 930 businesses across the globe in various industries.

2.6 Summary

The term of Analytics has been conceptualized in this chapter by describing various definition and perception from different Analytics experts reviewed from the literatures. Important to note, the use of words "Analytics" and "analytics" in this thesis refers to its *industry context* and its *technology context,* respectively. The evolution to Analytics semantic was started from the emergence of DSS in 1960s, data warehousing in 1990s, to Business Intelligence and Performance Management in 2000s. Analytics seemed to be distinctively classified by different Analytics experts. Eckerson (2011a) has distinguished Analytics as *deductive* and *inductive* Analytics. Other experts have classified Analytics in threefold; *descriptive, predictive*, (and *prescriptive) Analytics*, whereas predictive and prescriptive Analytics are often acquainted as *advanced Analytics* (Davenport & Harris, 2007; Lustig et al., 2010). Four business case studies from four different companies have been presented to learn from their business failure when those companies neglected the dynamic economy changes nowadays. Accordingly many organizations may call for the Analytics insights in order to tackle their business challenges. These organizations need to realize that applying Analytics entails several new opportunities such as *better customer insights, faster production innovation, optimized supply chains, agile financial performance*. At the same time, Analytics poses some challenges i.e. *data issues*, *expertise issues*, and *cultural issues*, that the organizations must be aware of upfront before they decide to employ Analytics in their daily business activities.

Chapter 3
OPERATING MODEL ONTOLOGY

"Drive thy business or it will drive thee. "
~Benjamin Franklin

3.1 Introduction

As the main research purpose to build a conceptual adoption model, another theory or model is necessary to be examined to lay a solid foundation for the development of the new model. The concept of operating model has been opted to inspire the construction of ADOPT-model, as to appropriately facilitate the organizations in adopting Analytics. First, a set of literature is reviewed in Chapter 3.2 to describe the need for a tool to sustain the organization's competitive advantage and how it is linked with the business and IT. Correspondingly, the ontology of the operating model is explained in Chapter 3.3 as to align the business side and the IT side. Different kind of operating models, which can be found in Appendix B, have been contemplated and then the general objectives of those operating models are described in Chapter 3.4.

3.2 Sustainable Competitive Advantage

Enterprises today are confronted with multitude of changes, such as mergers, acquisitions, novel technologies, shifting powers in the value chain, deregulation of international trade, privatization of state-owned companies, and many others (Op 't land, Proper, Waage, Cloo, & Steghuis, 2009). These changes are the ramifications of such environmental changes that resulted from the economics of information and the increasingly dynamic and global nature of competition (D'Aveni, 1997; Evans & Wurster, 2000). Therefore, enterprises need to be able to innovate and to have a desire to be proactively exploiting those innovative developments in order to create new business opportunities. Enterprises need to adapt themselves to the changes and seize opportunities in the volatile economic environment (Op 't land et al., 2009). Dijksterhuis et al. (1999) has pointed out that organization survival depends on how an organization foster the construction and integration of knowledge in adapting to the environment as well as how it stimulates the environmental changes through corporate knowledge and practices (Dijksterhuis, Bosch, & Volberda, 1999). Due to these environmental changes of the organization (outside-in) and changes in the organization itself (inside-out), Op 't land et al. (2009) has stipulated that organizations need to permanently improve and adapt their organization's strategy since the execution of a strategy is a continuous process as well.

As an organization needs the commitment from management team to successfully execute a strategy, the role of this top management is crucial for organizational changes. However the changes should not be invented merely by the senior executives, but the essence should be communicated to the whole organization. Zagotta and Robinson (2002) have conveyed that the real value of a strategy can only be recognized through strategy execution. A study from 275 portfolio managers has cited that the most important factor to shape management and corporate valuation is the strategy execution, despite the quality of the strategy itself (Kaplan & Norton, 2001). Johnson et al. (2003) has identified that organizational change programs should be active and vivid otherwise employees might see those changes as very little signified rituals. This imposes the management team another major challenge more than only the complexities of volatile situation and their consequences, as well as diverse stakeholders and their concerns (Op 't land et al., 2009).

Environmental changes experienced by organizations are characterized by obscure organizational boundaries and face-paced change (Gangadharan & Swami, 2004). Accordingly, organizations are forced to operate in complete new ways and they need appropriate decision support infrastructure to handle these challenges. Doherty et al. (2003) examined the applications of information technology and information systems employed by organizations to be the key drivers for supporting organizational daily operations as well as the decision making process including its strategic position. However, there is no single IT application or system that could deliver sustained competitive advantage (Henderson & Venkatraman, 1993).

The capability of an organization to leverage IT functionality on a continuous basis is critical to attain competitive advantages, rather than how sophisticated a technological functionality is. Organizational capabilities which to exploit the technology are used to differentiate the organization with its competitor. A fundamental change in managerial thinking is required to support and shape business strategy decisions through the role of IT in organizational transformation and IT strategic perspective (Henderson & Venkatraman, 1993). Rau (2004) recognized that the effectiveness of IT governance depends on how senior management communicates their business strategy to and interacts with IT leaders to ensure the technology investment enable those strategic purposes in effective and efficient manners. Nevertheless, business strategy should be reassessed when a new technology or new capabilities of antecedent technology are created in order to be able to offer new value to the organization. Business strategies and information system of an organization are interdependent where senior management should be involved in the IT decision making process and keep IT team informed of any changes made in business strategy (Pearlson & Saunders, 2004). Advert to abovementioned complex challenges and business-IT alignment, organization need a new instrument to accommodate their management in decision-making and in governance tasks (Op 't land et al., 2009). Above that, the constitution of IT systems must support the future company to achieve a tenable return on investment (Lynch, Diezemann, & Dowling, 2003).

3.3 Operating Model as Corporate Alignment

An organization builds a substantial foundation for execution by selecting certain processes and IT systems to be standardized and integrated (Ross, Weill, & Robertson, 2006). Once routine business activities become automatic, the outcomes turn to be predictable. Hence the execution should be efficient and the foundation for execution can take on another layer. Ross et al. (2006) captured two key concepts to be mastered.

First, the *operating model* presents indispensable level of business processes to be integrated and standardized across organization to deliver goods and services to customers. The integration contemplates common understanding across diverse business units to enable end-to-end processing to the customer. Therefore organizations need to be straightforward in deciding about the importance of process integration. For instance determining to what extent different business units share data. Likewise for the business process standardization where the management must determine for example, the extent to which same processes will be performed by which business units on the same way. On one hand, the process standardization can create efficiencies across business units. But on the other hand, it limits the possibilities for services customization. In the end, an operating model requires a commitment from an organization to operate its business.

Second, the *enterprise architecture* organizes the logic of business processes and IT infrastructure while reflecting the integration and standardization requirements from the organization's operating model. The enterprise architecture is signified not only to fulfill enterprise immediate needs, but rather to create a long-term view of the organization's business processes, technologies, and systems. The congruent strategic view enables individual projects within organization to build own capabilities. An organization can engage an operating model in creating the operational vision, in which key architectural requirements can be defined by business leaders together with the IT leaders, for the foundation of execution.

Henderson and Venkatraman (1999) argued that the incompetence of realizing the value from IT investments is partly due to the lack of organizational alignment between business- and IT strategies. They established a concept of strategic alignment that underlies two fundamental assumptions; that the management ability to create strategic fit between external and internal domains is directly related to economic performance, and that the strategic fit is inherently dynamic. The strategic choices determined by an organization ask for responses in which subsequently requires actions. Accordingly, strategic alignment is considered not as an event but rather as a continuous process of adaptation and change. Allied to this, Chan et al. (2006) perpetuated the previous study that the business- and IT strategy alignment leads to increased performance due to more focused and strategic use of IT in realizing the business values. The implementation difficulties of a system can be explained by misalignment as formal strategies are often only implemented at the upper level of the organization, and the lower levels translate business unit goals into personal goals. However, the strategic alignment is ideally to be present at all levels of the organization, i.e. across organization, system level, project level and individually (Chan & Reich, 2007).

3.4 General Objectives

The term of operating model has been conceptualized to formally represent the existence of the knowledge in certain area of interest, and the relationship that account among them (Genesereth & Nilsson, 1987). A set of representational definitions is reviewed in Appendix B from different advisory organizations to describe the ontology of an operating model for practical purposes, albeit another relevant conceptualization of this term can hardly be found in scientific literatures.

The representation of an operating model thus far shows the key ideas how organization components can be arranged together to execute predefined business strategy in delivering value propositions to the customers. Relevant organization domains often encompass business processes, organization, technology, system, and people. The operating model is typically linked to the organization's business model strategy, which delineates business goals an organization wish to target, as well as the association among the operational units and the guidelines to achieve economic value in the targeted market.

3.4.1 The "as is"- and "to be"- states

As the operating model drives the necessary level of integration and standardization within business processes (Ross et al., 2006), it is often considered as a medium to describe how the organization currently is doing its business, or well-known as the "as-is" operating model. Certain conditions can be derived or translated from its current situation to define the new target or "to-be" operating model. The target operating model sensualizes the high-level requirements that drive the future business and technology architecture design (Ross et al., 2006). In terms of business architecture, an operating model informs the organization of possible unique value propositions, which capabilities are required, and which distinct market entities are faced by the organization. In terms of technical architecture, an operating model informs IT and other support services of how diverse technical and business elements should be designed and implemented. Additionally, the value and appropriateness of shared services and related service-level agreements are enclosed as well in the operating model.

3.4.2 Dialogue between Business and IT Sides

Practically, an operating model is accounted as a suitable tool in the dialogue between business and IT. The dialogue often takes place at the top level management which is included the architectural alignment, business transformation, and the value and improved performance offered. This kind of dialogue allows IT management to utilize the operating model as a connection wire to derive business strategy to more concrete plans in the form of IT projects (Rosing & Rosenberg, 2011). However a business operating model can be generally described as a representation of traits that an organization is pursuing to complete various operational tasks or business-related activities. It could include strategic planning, stakeholders' relationships, and internal guidelines or standards. Above that, an operating model allows organizations to enhance their capabilities by repeatable processes without reinventing identical wheel for each business opportunity.

3.5 Summary

Due to the face-paced environmental changes experienced by organizations today, organizations attempt to continuously sustain their competitive advantage. They are forced to adapt in the volatile economic situation, however Henderson and Venkatraman (1993) have stipulated that there is no single IT application or system that could deliver sustained competitive advantage. In contrast to that, a fundamental change in managerial thinking is requisite to support the organization in tackling business challenges and upon this, competitive advantage is endeavored to be achieved. In response to this, several organizations have built an operating model to bridge the business needs with the enabling technology within their IT department. As these models present the organization's current situation ("as-is") and the desired future states ("to-be"), the adoption of Enterprise Analytics is also accounted to necessarily have the dialogue between the business and IT sides. However, other elements still need to be added and arranged to generate a desired new adoption model. Despite this, the essence of operating models has inspired the development of ADOPT-model that is elaborated in the next chapter.

Chapter 4
ENTERPRISE ANALYTICS ADOPTION MODEL

"After all is said and done, more needs to have been done than said."
~Neil Mason

4.1 Introduction

Responding to the high competitive market in today's economic situation, gradual improvement is no longer considered as sufficient aid to keep the pace with other peers. Business performance is indispensable to be enhanced substantially to deliver profitable result to the organization. Business process transformation may yield significant benefits to the organization but instead of seeing at individual processes or business units as islands, a holistic view of various levels within organization should be pointed at. Considering overall benefits and opportunities across enterprise and driving out waste from the structure of the organization until the end-to-end value chain that serves their customers. Analytics enables organizations to enhance their decision making process based on facts, while data needs to be gathered across the organization to generate valuable insights for their business.

This chapter explains the synergy of Enterprise Analytics domain being translated in an adoption model inspired by the conceptualization of the operating models discussed in previous chapter. It has created a conjoint of several adoption phases in the perspective of different organization components, envisages organizations with the focus on the entire governance to generate optimal benefits for them. Correspondingly, the Enterprise Analytics adoption model was conceptualized through the remaining sections of this chapter. The implication of this model is explained in Chapter 4.2, and then followed by the representation of the initial design of the conceptual model and its value propositions. In addition, other framework related to the ADOPT-model is presented in Appendix C in order to support the execution and to provide a better understanding to apply the conceptual model.

4.2 Conceptual Design

The general purpose of the creation of a conceptual model was to provide an organization with a (single) generic overview of an overall structure in the adoption of successful business Analytics and to represent the prerequisite actions in terms of organizational components within gradual phases. This conceptual design was aimed to facilitate the starting phase of the adoption process that is undertaken by an organization within enterprise wise.

An operating model comprises a high level view of how diverse organizational elements interact to support the business, as well as the target operating model that describes how those organizational elements could be arranged to achieve optimum efficiency during the adoption process. It identifies also where to prioritize change activity to accelerate the acceptance of Analytics across organization.

Both facilitating and inhibiting factors were attempted to be red-flagged in the description of the model to create an awareness or extra attention from stakeholders of the organization. Nevertheless, applying this model requires an alignment between the business and technology sides.

4.2.1 What is Enterprise Analytics Adoption Model?

An enterprise Analytics adoption model can be represented as a holistic 'organizational system'. This model enables the practical execution of organization's strategic views by mapping how and when the organizational elements are to be coordinated in adopting and enhancing organization's Analytical capabilities. As aforementioned in early chapter, the model took into account four different perspectives of organizational elements namely the organizational *structure*, business *processes*, *people*, and *technology*. Organization's strategic objectives are translated into a coordinated set of execution activities in terms of those four organizational elements. The model endeavors to assure that the organizational adoption of transition develops with an optimal communication and coordinated alignment among those elements.

Interaction between organizational components needs to take place constantly to ensure the coordination of the transformation program. Therefore the model has been built to map all critical activities for an organization to be aware of specific situation in order to progress. The executive board members, business owners, directors, and managers designate this model to ensure the organization does not escalate negative situations or lose courage when they have no clue what is going on. Corporate vision can be translated into the model to aid the managers to provide more information and clarification on the corporate missions. In order to better communicate the initiative to the lower level employees, managers could reinforce the values and behavior found most acceptable by the organization. For large enterprises with multiple divisions or functional units, they may need the model to promote the initiative's environment where each employee acts as a part of the adoption process and understands his/ her role by position him-/herself in a particular situation on the model. Furthermore, the model helps organizations to eliminate unnecessary tasks or activities that may cause in wasting organization's economic resources e.g. human resources, wasted implemented system, etc.

In a nutshell, this model can be considered as the *blue print* of Analytics adoption process in guiding an organization to achieve or improve their analytical capabilities. The following paragraphs discuss the notion the conceptual enterprise Analytics adoption model and the development of its representation.

4.2.2 Initial Design of ADOPT-Model

The scope of the proposed Enterprise Analytics adoption model was to clearly map the prerequisite activities to set up the Analytics capability embedded in the structure, people, processes, and technology of the organization during the adoption process. As in the preliminary design phase, the proposed model was depicted as on the *x*-axis with five consecutive adoption phases, on the *y*-axis with four organizational elements, which have been derived from Accenture's business operating model (see Figure 4), and the relationships between both axes. The preliminary proposed model is represented in Figure 13.

This proposed model has been granted with an acronym of "the ADOPT-model". As it can be seen at figure below, each of the organizational elements has a *bidirectional relationship* with each of the adoption phases. On each intersection of ADOPT-model, its development endeavors to capture the essential operations need to carry out to assure an effective Analytics adoption across the organization. These activities were mapped into the dotted-line boxes found upon collected secondary data in the early phase of the research project and researcher's logical reasoning.

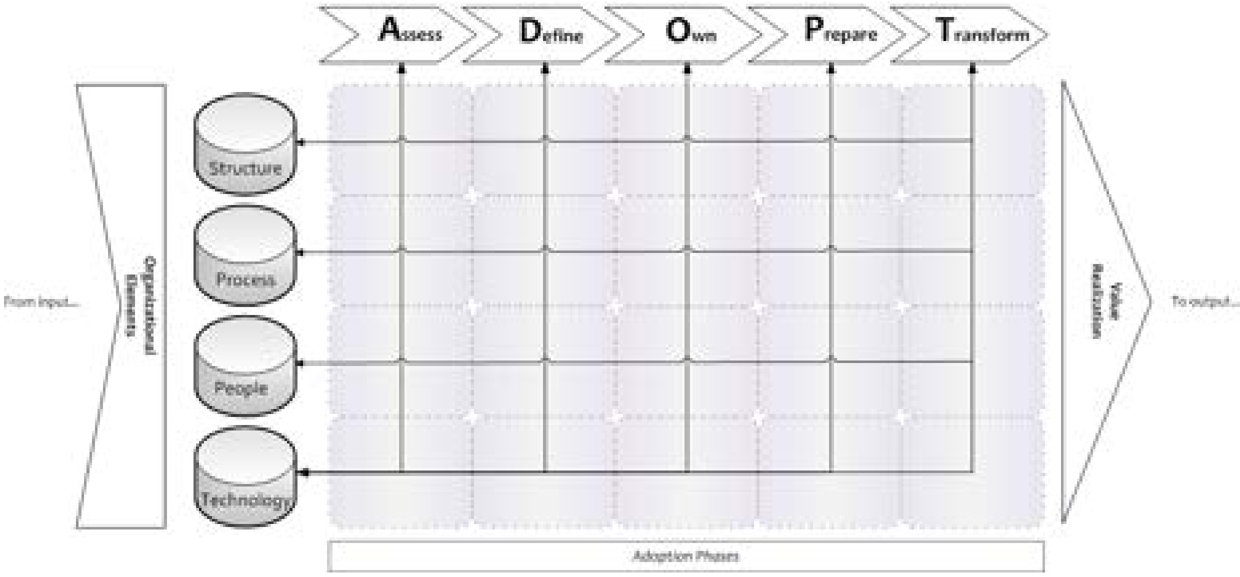

Figure 13. Preliminary design of ADOPT-Model

As aforementioned, this model serves as a blue print to provide a generic overview of the Analytics adoption process across the organization. The representation of each box should cover the crucial activities needed to be executed in consecutively manner from the most left positioned boxes to the right side. While applying this model, each box can be jotted down into a lower or detailed level. The entire adoption process should take into account all four organizational elements to enable organization's value realization where the value of the Analytics insights can be assessed upfront and the business benefits can be realized over the time. The adoption phases comprehend five essential common operations for each organizational element that are systemized and described in the subsequent table.

ASSESS	Assess the organization's Analytical maturity level and find the gaps in the present state (As-Is)
DEFINE	Define organization's Analytical maturity level and define the desired state in the future (To-Be)
OWN	Own the alignment between the corporate vision and Analytics value proposition
PREPARE	Prepare the Analytical environment to set up desired capabilities across the enterprise
TRANSFORM	Transform the desired business value to organization's owned Analytical capabilities as performance delivery and implementation

Table 1. Description of each adoption phase

The proposed model attempted to apply all above common operations to the organizational elements. The necessary activities identified for each box in the proposed model are further elaborated in the terms of organizational *structure, processes, people,* and *technology*. The notion of the complete initial ADOPT-model model can be found on the following Figure 14.

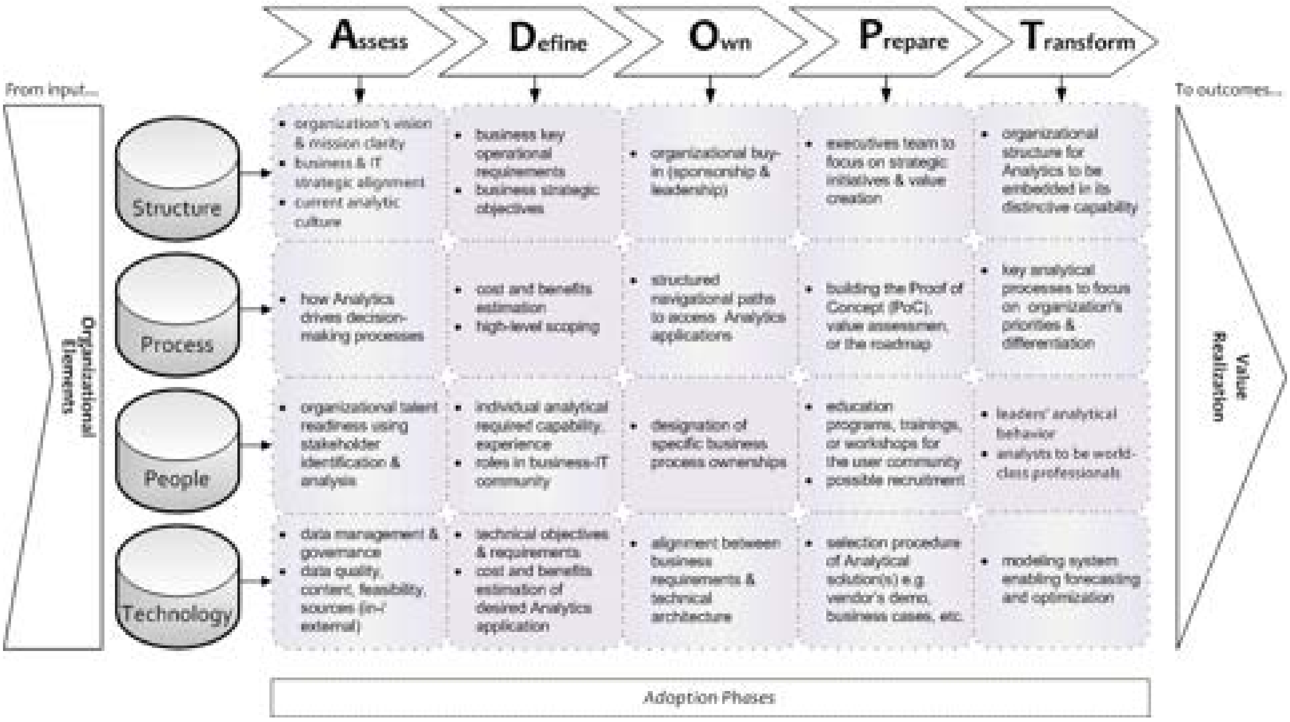

Figure 14. Initial design of ADOPT-model

STRUCTURE

The type of organizational structure has an impact on Analytics adoption rate. Moreover, this element comprehends organization's environment, culture, and strategy as well. As organizational structure depends on current organization's strategic objectives, it is necessary to *assess* in which manner and to what extent various roles, power, and responsibilities are delegated, coordinated, and monitored amongst organizational members. Hence, the organization needs to inquire its vision and mission, and how those are aligned with the supporting technological side. Nonetheless the organization's culture is considered to be partly of the structure as well as in people organization. Possible existing Analytics capabilities need to be identified to recognize the Analytical culture within an organization; how analytical capabilities are distributed in the organization, silo-based (decentralized) or enterprise-wide (centralized), how the upper level management agitate for adopting Analytics. Further, the organization may *define* the future state in the sense of business key operational requirements and also its new strategic objectives. It is remarkably important to *own* sponsorship and leadership from the upper level management to support Analytics initiatives. An executive team should be formed and *prepared* to focus on the strategic initiatives and business value creation before the *transformation* of organization's distinctive capabilities can take place.

PROCESSES

Various process-related streams should be *assessed* to identify any process gaps or process overlaps in order to optimize those processes. First, the organization must recognize what the foundation is of their decision making or how Analytics drives their decision making; fact-based and cross-functional, or using gut feeling and siloed, or any combinations of those? However the scope of desired optimal processes must be *defined*, and based on that the business added values and costs can be estimated. To ensure the desired decision making process, the organization must *own* structured navigational paths for end-users to access the Analytics applications. An organization may opt to leverage the Web or customizable information portals which are dominant strategies to disseminate application access. In prior to the real transformation, the *preparation* may undertake a fractional execution of selected Analytical solution but in smaller case or very limited scope e.g. proof-of-concept, value assessment, or roadmap. During the *transformation* the focus lies on organization's process priorities and differentiation.

PEOPLE

Assessing the structure of an organization can be seen as partly *assessing* the people organization as well, albeit underlining the upper level management of the organization. The people element here stretches out to stakeholders of the organizational network. After the stakeholders are identified and analyzed, the organization ought to *define* individual analytical capability and experience in terms of the roles that are required and how they are related to each other within business-IT community. These roles can perform the business- or IT processes individually, in groups/ teams, in departments, or job roles within an organization. The organization could assign the *own*ership of certain processes to specific roles as the process owners. When organization has captured which roles need to occupy, potential analysts are prepared by providing educational programs, workshops, or trainings. If there is no in-house analytical talents that are required in the transformation program, the organization may recruit external talents. Leaders are transformed to behave analytically and passionate for analytical competition, whilst analytical amateurs are transformed to be the world-class professional analysts.

TECHNOLOGY

This organizational element encompasses technological systems, tools, and particularly, the data. The data governance and management ensures data is accurate, consistent, complete, available, and secure. Therefore it is prominent to *assess* how the organization governs the data and manage it. As data governance comprehends not only technology but also people and process elements, these three elements are strongly related in determining the quality of data which valuable insights can be extracted from. To support capturing, storing and extracting good quality of data, an organization should bring in a properly information system providing Analytical solution. Prior to the system selection, the technical objectives, and requirements need to be clearly *defined* which underlie the design of technical architecture. This architecture design ought to be aligned with the predefined business requirements derived from organization's strategic view. The implementation of a new system can be *prepared* by carrying out the selection procedure for Analytical solution from possible several vendors. The *transformation* to the new modeling system enables forecasting and optimization based on comprehensive statistical modeling or calculation.

4.2.3 Value Propositions of ADOPT-Model

The existing business operating models have been used to provide the way how business is organized to deliver product or services to the customer. In analogy to those operating models, the proposed ADOPT-model is to provide how organizations elements are arranged to enhance organization's analytical capabilities. It goes beyond the primary phases that are merely describing the "as-is"- state and defining the "to-be"-state. Hence, it covers more in a high-level and complete overview started from the emergence of Analytics initiatives until the organization's analytical capabilities are transformed completely.

In addition, leveraging the proposed ADOPT-model could deliver several added values to an organization. A ramification of the proposed organizational transition can be clearly mapped and visualized. On this manner, gaining organizational buy-in can be done more straightforward as well as managing the stakeholders' expectations. Potential iterations on specific activities ensure a robust baseline for the implementation planning and tracking as in developing a vigorous business case, viable roadmap, or Proof-of-Concept (PoC). Prior to the actual adoption of Analytics, the ADOPT-model provides the organization with critical path analysis in assessing the current state. Any operational gaps are plugged and any overlaps are eliminated. Organizational improvements can be assured to evolve continuously. However, the proposed ADOPT-model has been essentially accounted as the means in communicating the transformation program to the group of stakeholders.

4.3. Summary

The core of the presentation of two previous chapters has been conjoined and resulted the development of an Enterprise Analytics adoption model, or the ADOPT-model. As the main research purpose to design a new adoption model, a set of key activities in setting up Analytics capabilities has been mapped into the ADOPT-model. These activities have been formulated based on the secondary data sources during a desk research that was conducted in the early phase of this research project. The ADOPT-model comprises five adoption phases, which are the *Assess-, Define-, Own-, Prepare-,* and *Transform* phases on the *x*-axis, and the four organizational elements on the *y*-axis, i.e. *Structure*, *Process*, *People*, and *Technology*. As this is the initial design of the adoption model, the ADOPT-model has been further evaluated and verified by applying certain data collection and analysis, which are discussed in the next chapter.

Chapter 5
DATA COLLECTION & ANALYSIS APPROACH

"In God we trust. All others bring data."
~ W. Edwards Deming

5.1 Introduction

Relevant data was gathered through a desk research and literatures study during the early phase of the research. This type of *secondary data* was originated from journal documents, scientific articles, white papers, best practices, web sites, and knowledge database via the enterprise portal. Information gathered from the secondary data underlies the initial construction of the EAAM conceptual design. Further, this model has been evaluated and refined during the *primary data* gathering through qualitative interviews with field experts. The verification of the conceptual model was generated as well from the information gathered from the primary data source. Next section elaborates the chosen qualitative data collection approach and the rationale behind it. A number of required characteristics for appropriate interview respondents were classified in two different types and specified in Chapter 5.3. Subsequent section explains how the data collection was organized and how the procedure took place. At the end of this chapter, an approach to analyze the collected data is introduced before the research outcome is presented in Chapter 6.

5.2 Qualitative Approach Using Interviews

The nature of this research pertains to be exploratory and the adoption of Enterprise Analytics at that point was still at the level of initiatives development, as recalled from Chapter 1.3. An exploratory study is often undertaken when the situation at hand is not yet much known (Emory & Cooper, 1991; Sekaran & Bougie, 2009). Therefore, an extensive preliminary work needs to be carried out in order to gain acquaintance with the phenomena in the situation. This is aligned with the aim of this research project which was to investigate the subjective interpretation from respondents and to gain understanding in problem context in order to provide solution on the 'how'-question stated as the main research question. Moreover, qualitative interview is a frequent applied method in social-science or business-related studies (ESDS, 2011).

5.2.1 Rationale behind Interview Methodology

Multiple *semi-structured interviews* with *open-ended questions* have been opted as the appropriate primary data collection approach. More in-depth understanding with regard to the problem at stake can be obtained from the actual situation. Out of the experiences gained by the field experts, the researcher could search for notable insights that can facilitate the finding of solutions to the research problem. The questions have been formulated as open ended allows the discovery of specific information supplied by respondent that the researcher would not have thought previously to be relevant, whilst the semi-structured interview allows the flexibility for the researcher as well as respondent to define the themes to be further explored. On that account, both respondent and researcher are not demarcated to pre-defined topic of interest which can be contradictory to the nature of exploration itself.

According to Arksey and Knight (2009), this type of approach is a valuable research method for exploring data on understandings, opinions, attitudes, deeds, and feelings from people who have in common. Since the individual is accounted as the unit of analysis for this research, several people who have common experience in doing Analytics projects are considered as valid potential interview respondents. A *face-to-face interview* was highly preferable to conduct the session. Much more detailed information is available through interviews than other data collection methods, such as surveys. Any visualization regarding the topic of interest is easier to explicate. Respondents may feel more comfortable having a conversation with the researcher about their experiences as opposed to filling out a survey. Also any unclear questions arise during the interview can be explained or clarified directly by the researcher.

Another proponent of this approach, Gubrium and Holstein (2001) has a perception that diverse qualities and meanings owned by the respondent can be exploited by the researcher to explore these and respondent's social organization. Agreeing on this idea, the researcher seeks two-sided perspectives on how the *client organizations*, which have direct impact of business value added, and the *consultants*, who have indirect impact of business value added in transformed organizations, were sensing the process of transformation. This way, the conceptual design of EAAM could be underpinned with more vivid construction. However, qualitative research using interviews is prone to bias and time-extensive (Sekaran & Bougie, 2009; Verhoeven, 2008). The interviewer must be trained and possess the appropriate interviewing techniques or skills. Moreover, generalizability is difficult to attain for small sample, which was the case in this research project.

5.3 Respondents Selection

The potential interview respondents were classified in two different types of field experts: the *consultants* from Accenture/ Avanade (which is a joint venture company between Accenture and Microsoft), and the representatives from *client organizations*. Before approaching potential respondents, selection criteria were formulated in a priori for each type of respondent. The selection criteria for consultant-respondents and client-respondents are presented in Table 2 and Table 3 respectively.

I. CONSULTANTS	a. The respondent should have an advisory role within the organization he/she works for
	b. The respondent has gained the experience working in any Analytics-related (DM/BI) project(s) or owns the knowledge around the area of Analytics adoption
	c. The respondent can provide a significant contribution to the subjects at question

Table 2. Selection criteria for consultant-respondents

A group of consultants, with different functional roles ranging from analyst, manager to senior executive, were approached to participate in the interview session.

The information gathered from this type of respondent is primarily to verify the initial concept of EAAM and secondary to provide information to unravel the research questions RQ1 and RQ2 (see Section 1.2.3). Since Analytics projects were still infrequently carried out in the Netherlands, therefore there were very much limited resources of information to find. Referring back to the entire discussion presented through Chapter 2, Analytics term still cannot be defined by a single or universal description that is accepted by everyone. However, many of the experts in this study field have acknowledged that a proper way to manage data in the organization is prerequisite to enable the adoption of Business Intelligence. After having these in places, the way towards Analytics adoption is then possible to undertake. These reasons underpinned the selection criteria to question a group of consultants who also have expertise in the area of (Master) Data Management and Business Intelligence. Possible causality relationship happened here can be taken into account in explaining the inhibiting aspects that withhold organizations from adopting Analytics. Nevertheless, consultants who have more expertise in the study field such as BI were still considered to have significant contribution to the verification of initial conceptual EAAM by reflecting BI adoption as analogous project to Analytics adoption.

II. CLIENTS	a. The respondent is a representative from an organization located in the Netherlands
	b. The respondent is selected from different organizations across industry sectors
	c. The respondent is a representative from a medium-to-large enterprises or a fast-growing company
	d. The respondent should have a highly involvement in the business- and IT activities, and in decision-making processes
	e. The respondent has the knowledge or understands his/her organization's business- and IT landscape
	f. The respondent can provide a significant contribution to the subjects at question

Table 3. Selection criteria for client-respondent

Another respondent group, the clients, was questioned to ratify the information provided by the consultants with an emphasis in responding to research questions RQ1, RQ2, RQ3, and RQ4. The client-respondent could be a *business/ IT sponsor* takes part in an executive steering in organization committee or could be the *business/ IT driver*, whereas in large organization a (middle) manager is delegated to be responsible for tactical and/or operational processes but should still possess the same characteristics as the sponsor. The client-respondent could also be from technical resources that understands the business or from business resources that understand technology. Possible functional roles are for example the CxO, business/IT (senior) manager, ambassador in company's reporting, other business/IT executives.

Due to confidentiality requirement or non-disclosure agreements between the respondent and related organization, the information gathered was processed anonymously. However, types of industry where respondent's organization operates in, services they offer, and the functional role of respondent have been accounted as the differentiator between one respondent and another. In addition, a few companies across different industries was intentionally aimed to be investigated in order to see whether significant traits can be identified based on the type of industry. The total number of interview sessions conducted based on aforementioned selection criteria is 18, which comprises 12 interviews with consultants and 6 with clients. All respondents are listed in Table 44.

Name of Respondent	Industry Sector	Type of Services	Functional Role	Date of Interview
Consultant A	Consultancy	Management consulting, technology and outsourcing services	Manager BI	20-06-2012
Consultant B	Consultancy	Management consulting, technology and outsourcing services	SAP BI consultant/ analyst programmer	21-06-2012
Consultant C	Consultancy	Management consulting, technology and outsourcing services	Manager BI	21-06-2012
Consultant D	Consultancy	Management consulting, technology and outsourcing services	Manager BI	22-06-2012
Consultant E	Consultancy	Management consulting, technology and outsourcing services	Manager DM	22-06-2012
Consultant F	Consultancy	Management consulting, technology and outsourcing services	Manager BI/ Analytics	22-06-2012
Consultant G	Information Technology	Business and technology services	Senior Consultant	25-06-2012
Consultant H	Consultancy	Management consulting, technology and outsourcing services	Senior Manager BI	26-06-2012
Consultant I	Consultancy	Management consulting, technology and outsourcing services	Manager BI	29-06-2012
Consultant J	Consultancy	Management consulting, technology and outsourcing services	Manager BI	29-06-2012
Consultant K	Consultancy	Management consulting, technology and outsourcing services	Consultant BI	29-06-2012
Consultant L	Consultancy	Management consulting, technology and outsourcing services	Senior Executive BI/ Analytics	05-07-2012
Client A	Internet payment	Internet payment processing, clearing & settlement, fraud prevention	Head of business developer	06-06-2012
Client B	Insurance	Investment, assets and insurance	Business Architect	22-06-2012
Client C	Insurance	Travel and cancellation insurance	Chief Financial Officer	28-06-2012
Client D	Utility	Gas and oil	BI Centre of Excellence Lead	29-06-2012
Client E	Utility	Natural gas	Coordinator portfolio Optimalisation	29-06-2012
Client F	Utility	Energy (gas and electricity)	SAP BI/ Portal team manager	02-07-2012

Table 4. Interview respondent list

5.4 Operationalization

The entire data collection process has been constituted to serve the purpose of evaluating the conceptual adoption model proposed in chapter 4, and to get familiarized with Analytics market situation in the Netherlands. According to Verhoeven (2008) an *operationalization* is the step of translating the research questions into observational questions to be employed as a tool for collecting data. Prior to the data collection, two customized protocols were formulated for each type of respondent. These different measurement instruments were created due to (slight) different purposes in collecting data and because the consultants and clients carry different perspectives concerning Analytics capabilities transformation.

The interviews with consultants focus on the proposed values from Analytics solutions. Unlikely, the interviews with clients focus on the perceived values from Analytics solutions. However, both type of observational questions were derived from the research questions and reflected from the conceptual EAAM. The interview protocols contain topics of interest that can be used to guide the conversation in a way to be more efficient but still flexible for exploration. The themes covered in both interview protocols have been systematically structured in the following Table 5. Additionally, the replications of actual interview protocols can be referred to Appendix E and F for the consultant-respondent and client-respondent respectively.

Theme	Consultants	Clients
I. Background information	Respondents' contact details, functional role(s) and work experience length are documented for practical purposes e.g. reporting back, getting feedback, or profiling interview result	Respondents' contact details and functional role(s) as well the organization's profile are documented for practical purposes e.g. reporting back, getting feedback, or profiling interview result
II. Current situation	Respondents are asked to describe an overview concerning the Analytics current market and trends, their Analytics projects, and what are the selling points of certain Analytics vendors they often consider in offering to clients	Respondents are asked to describe their organization's state-of-the-art concerning Analytics adoption, how they decide on (not) adopting Analytics, and how they select their Analytics provider
III. Model verification	Respondents are asked to provide feedback on the initial conceptual model, describe any inhibiting factors during the Analytics projects, and how to solve	Respondents are questioned about organization's current situation in terms of the four organizational elements (structure, process, people, technology) to be reflected in the conceptual model
IV. Pattern identification	Respondents are asked to identify similar characteristics attached to Analytics organizations	N/A
V. Barrier and risk	Respondents are asked to enumerate which concerns are mostly anticipated before adopting Analytics	Respondents are asked to enumerate which concerns are perceived during Analytics adoption
VI. Success criteria	Respondents are asked to provide the success criteria to adopt Analytics from lesson learned previously in terms of the four organizational elements	ditto
VII. Closing	Respondents get the opportunity to make additional comments or ask questions regarding the research projects, and researcher shows gratitude to respondent for their participation	ditto

Table 5. Interview's themes

5.5 Data Management

First of all, confusion that might emerge from the title of this section needs to be avoided. This section implicates data management as the entire process taking part of this research project, from drawing near the prerequisite data sources, collecting, processing, analyzing, until substantial ramification of data results are obtained. Rather than referring to Data Management that relates to the area of data warehousing, information/ data architecture, which is considered more as the domain of the research topic. As the name confusion has been put aside, this section focuses around the process of interviewing and next section (chapter 5.6) elaborates the analysis of data obtained.

Potential respondents were mainly approached through network referrals within prior-selected-respondent's social network or through so-called " snowball" process (Gubrium & Holstein, 2001). An invitation letter (see Appendix D) to participate in the interview session was sent to each potential respondent. Afterwards, an interview session was planned and the relevant interview protocol contained a question list (Appendix E and F) was shared to the respondents. All interview sessions were conducted through face-to-face meetings, with an exception of one interview session with Client E (see Table 4) due to inconvenient traveling time that exceeds 1.5 hours (one-way) by car. Instead, a phone call session suited better to be carried out considering the practical reasons. Duration of each interview session ranged between 45 to 75 minutes. The locations where interview sessions were held are at Accenture ITO-office, at TU Central Library Delft, and at clients' site.

Interview protocols and respondent selection were set up prior to the execution. Each interview was fully audio-recorded with respondent's consent, and field notes were taken occasionally during the session when necessary. All information gathered during the interviews was processed and translated into non-literal transcripts. The transcript comprehends a summary of discussed subjects during the session as well as the themes emerged along data processing. Every transcript was sent back to the related respondent for a review or "validity check", and for possible corrections or adjustments. After the final approval attained from the respondent, the non-literal transcript is further processed to be analyzed. When software tool is used in analyzing qualitative data, the researcher can benefit a reduced analysis time, more systematic and explicit procedures, flexibility and revision during the analysis procedure(Tesch, 1989). For these purposes, a computer-aided tool for qualitative data analysis called NVivo10 was applied. Further approach to the analysis of gathered materials is explored in next section. Moreover, the audio-recorded materials will be terminated once the research report is finalized and the non-literal transcripts will be documented by the researcher for possible future research or investigation.

5.6 Data Analysis Approach

The proliferation of computer use to assist researchers in qualitative data analysis (QDA) does not imply to omit researchers' role in preparing the textual data (McLellan, Macqueen, & Neidig, 2003). The QDA software potentially offers tools to manage and process textual data more efficiently, however researchers are still necessitated to give a special attention in preparing, entering or importing, analyzing, and interpreting the textual data (Malterud, 2001). As aforementioned, the interviews sessions were translated to non-literal transcripts, which turned out to be 74 pages of text in total. These transcripts were further systematized and analyzed by applying an *applied thematic* *analysis (ATA)* approach. The typology of this approach and the rationale of the selection above other QDA approaches are elaborated in section 5.6.1. Taking this approach into a more precise practice, a thematic network technique is applied to facilitate the structuring and depiction of different themes emerged during the text exploration. A step-by-step process that guides the researcher unto the outcome of analysis is enumerated in section 5.6.2.

5.6.1 Applied Thematic Analysis

The ATA approach is a set of procedures constructed to identify and contemplate themes started from textual data in a way that is transparant and credible (Guest, MacQueen, & Namey, 2012). The thematic approach appears to be intuitive and straightforward. Accordingly this approach often appeals to novice researchers who are not very much familiar with in-depth theories and dealing with narrative data for the first time (Howitt & Cramer, 2008; Riessman, 2008). Higher involvement and interpretation from the researcher are required in applied thematic analyses, as in *grounded theory (Johnson, Melin, & Whittington)* approach (Guest et al., 2012). Both approaches carry similar methodological analytic frameworks. However they vary considerably in the manner in which themes, concepts, and categories are managed (Howitt & Cramer, 2008).

Grounded theory is designed to identify categories and concepts within the text by applying a set of inductive and iterative techniques to link into formal theoretical models (Corbin & Strauss, 2008; Glaser & Strauss, 1967). A systematic review of text data involves topics identification that are progressively integrated into higher order themes through de-contextualisation and re-contextualisation in GT approach (Corbin & Strauss, 2008). The key attribute of GT approach is placed in building theoretical models that are constantly checked against and grounded in the data, whilst ATA approch consists partly of this attribute (Guest et al., 2012). The theoretical models may and may not take place in applied research. Nevertheless, the ramification of both analysis methods is the researcher's interpretations that are supported by actual data collected.

Applied thematic analysis is considered as a rigorous, yet flexible and inductive approach (Guest et al., 2012). The development of the codebook should be systematic and iterative. The iteration takes place to revise researcher's initial intepretation according to the reanalysis of data from several angles. Since ATA does not preclude a construction of theoretical models, it does focus on describing and understanding the meanings that people give to their social reality and lived experiences. Guest et al. (2012) believes that a thematic analysis is still the most useful method to capture the complexities of meanings from a textual data set, and used as most common analysis method in qualitative research.

5.6.2 Thematic Networks

Before being able to conduct a thematic analysis, a particular technique is opted to organize qualitative material. *Thematic networks* is a technique that enables a methodical systematization of textual data and its presentation (Attride-Stirling, 2001). It allows rich-data exploration, yet sensitive and insightful and identify the underlying patterns. A number of steps needs to be taken prior to the construction of the thematic network(s), which is encapsulated in the following figure:

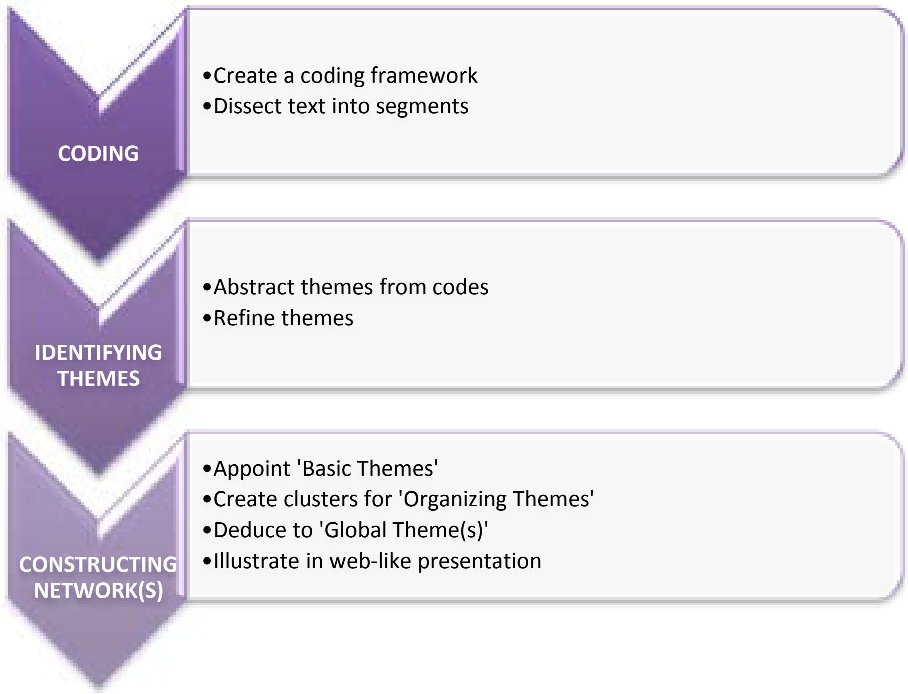

Figure 15. Steps taken in the textual analysis in ATA approach

Step 1. Coding the textual data

The first step made was reducing the data. After reading the interview transcripts several times and understanding the explanations given by the respondents, some recurrent issues were identified. These issues and a set of theoretical interests which was pre-formulated in the interview protocols, consolidate the coding framework to be employed. Based on the coding framework, the transcript text was dissected, classified, and organized into a set of 67 codes. These codes differ from each other to prevent data redundancy, yet significant enough to be meaningful.

Step 2. Identifying themes

Once all the text has been coded and re-read, the themes were abstracted within the context of the codes from the full text. The structure of the interview protocols assisted the re-formulation of the themes. A great deal of researcher's interpretations instigates the formulation of the themes to be discrete as well as representative for each text segment under which the codes were classified. The 67 codes and over 300 text segments, were reduced to 11 representative themes that cover all segmented text. The criterion of the theme selection was intended to provide explanatory value on the theoretical interests of this study, with an exeption of the last theme given in the table at Appendix H. The theme of *'most critical adoption phases to progress'* was quantified and presented in a statistical chart to create a conformation from all consultant-respondents, see further in section 6.3.5. In this manner, this last identified theme was omitted in the construction of the thematic networks, which is discussed in the subsequent step.

Step 3. Constructing network(s)

All themes derived from the full text were arranged into coherent groupings and assigned as *basic themes*. Some basic themes were clustered in the *organizing themes*, and further were grouped in the *global themes*. After all codes and themes were identified, the thematic networks were generated from the software tool NVivo 10 and performed throughout Chapter 6. The thematic networks comprise the presentation of the *codes* (ellipse-shaped), *basic*- and *organizing themes* (rectangle-shaped), and its *relationship* (diamond-shaped). A set of prescripts has been determined to include all codes in the thematic networks. The codes that were quoted only by one respondent are depicted with a smaller ellipse-shaped. However, those codes were approved when supported by a relevant and strong argument given by the respondent, which was justified by the researcher based on her knowledge built from the literature studies during the early phase of this research project. The normal ellipse-shaped codes were quoted more than once by the respondents and presented in a descending order with the most quoted code(s) be firstly discussed.

5.7 Summary

A *qualitative research* approach has been opted to carry out this research project. The data collection instrument chosen was to employ the *face-to-face interview* method with open-ended questions. The type of interview was semi structured with open-ended questions to allow the elaboration of interesting topics that may not be thought before by the researcher. The respondents were distinguished in two different groups, the *consultants* and the *clients*. Accordingly two interview protocols have been set up to guide the interview sessions, and both interview protocols can be found in the Appendix E and F. The text data resulted from those interview sessions were transcribed and analyzed by utilizing the *Applied Thematic Analysis* approach. Also the presentation of the analysis results was given through the visualization of the *thematic networks*.

Chapter 6
RESEARCH RESULTS AND ANALYSIS

"Not everything that can be counted counts, and not everything that counts can be counted."
- Albert Einstein

6.1 Introduction

After the audio-recorded interview sessions with experts have been transcribed into text data, this data was coded using the ATA approach as explained in section 5.6.2. Themes were identified and extracted throughout all text data and then further arranged into *basic, organizing*, and *global* themes as can be seen in Appendix H. These themes are presented in the visualization of the thematic networks throughout this chapter as well as the analysis results that are elaborated using those generated thematic networks. Firstly, the Analytics current market situation is explained in Chapter 6.2, which is also the first global theme identified during the text data analysis. The second global theme, the adoption process evaluation, is specified in Chapter 6.3. Subsequently, the verification of the ADOPT-model is explained in Chapter 6.4.

6.2 Analytics Market Situation

6.2.1 Analytics Adoption Areas

Many organizations have adopted Analytics across different functional levels. From the figure below, several functional areas were captured from the interview with the consultants. Some of the organizations have adopted Analytics within enterprise-wide, others have adopted in a single or more business unit(s). For example, a chemical company has adopted descriptive Analytics at each of functional level namely finance, supply chain, human resources, marketing, as a complete portfolio. In contrast to that, a utility company, banks, and insurance companies have adopted Analytics mainly for the *financial* purposes such as Order-to-Cash (O2C) and Purchase-to-Pay (P2P). These kinds of reporting are typically related to company's cash flows, balance sheets, or accounts receivable.

For the *supply chain*, logistics, and inventory management, Analytics provides the entire process chain reporting from the beginning such as gathering and metering information, production planning, until the end such as invoicing payment to the customer. Descriptive Analytics could also support the *Human Resources* department for example to store all company's incidents occurred with all information related to the people, costs, or to manage employees' scheduling. *Marketing* department could elevate the quality of company's client services by enquiring what the average time-to-wait is for the customer to open a new bank account, what the value of each transaction is, or how long it takes for the employee to process a transaction, etc.

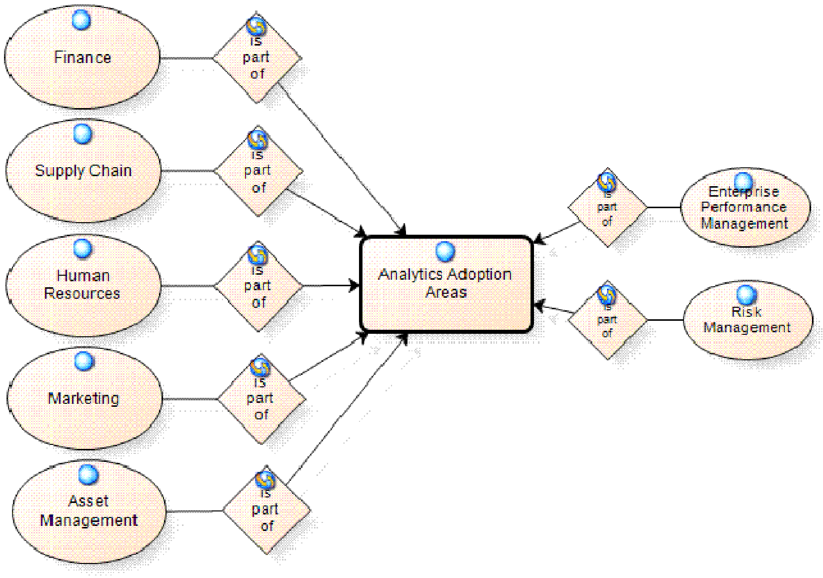

Figure 16. Thematic network for Analytics adoption in various areas

Predictive Analytics is mainly adopted at the operational level, for example the optimization of the transportation network of a logistic company, or for marketing/ brand management purposes such as customer analysis through survey data to create segmentation based on customer behavior. Another example is that an Alarm Call Centre could schedule better their employees by anticipating how many calls will be expected at a particular time, as well as banks and insurances companies need to mitigate their risks by applying Analytics in their *Risk Management* and/or *Asset Management*. For example, the system can predict the type and level of risk the bank/ company might carry when the customers fail to fulfill their mortgage obligation based on the customer segmentation. *Enterprise Performance Management* is included here since Analytics is often employed to support or extend organization's ERP system, albeit more people today begin to see Analytics as a standalone discipline.

6.2.2 Desired Analytical Capabilities

The key drivers for organizations that have adopted or are interested in adopting Analytics can be described in various ways. At least they are aware that Analytics can provide them a better understanding, tracking and monitoring of their business performance. These capabilities can facilitate the managers of the organization in their decision-making processes. This section attempts to envisage diverse Analytical capabilities desired by different organizations. It is also interesting to enlighten how these organizations underpin their desired Analytical capabilities by altering new vision for the people organization.

Large international companies are often dealing with immense flow of reports from local operating branches throughout the world. Synchronized global figures need to be distributed worldwide to their decision makers to be able to identify current opportunities and to get insights into their performance, globally or locally. In some cases, these companies need to find out whether a centralization or decentralization of datasets could generate business value for them more timely and effectively. A centralization of capabilities is set up to create common definitions to be used across global branches. For example, *a global span data analysis* can be employed for global purchasing or sales services. A utility company is currently carrying out a new vision for people organization to think more in the sense of which data they think that will be needed and be valuable for business to be stored. This involves creating the predominate KPIs e.g. for the up-stream's production, total produced gas, etc., before they generate different kinds of reporting or analysis or calculation.

At the end, any profit organizations are performing their business for the profit generation and *cost avoidance*. A good example from an organization that attempts to reduce their cost when their engineers and production technologists are spending 40-50% of their time in collecting data from different sources, cleansing and combining the data. These analysts should have spent their time to analyze the data instead of to organize and ensure the quality of the data. However, the organizations need to proceed in achieving the analytical capabilities. The figure below shows different desired capabilities in terms of descriptive and predictive Analytics perceived from the interview with the consultants and clients.

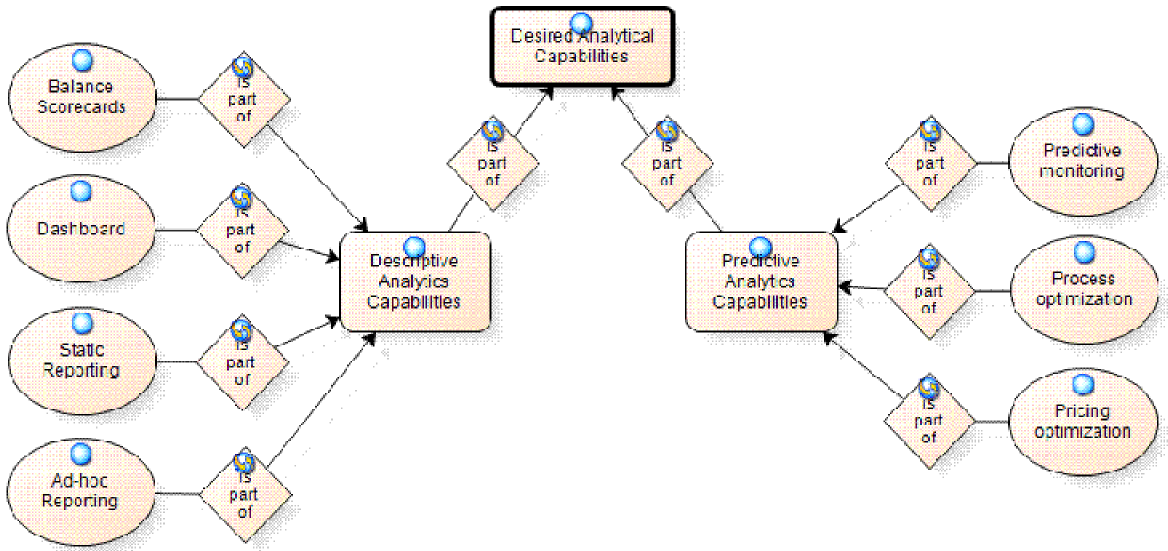

Figure 17. Thematic network for desired Analytics capabilities

Descriptive Analytics

Descriptive Analytics capability comprehends a reporting system by creating *balance scorecards, dashboarding, static-, and ad-hoc/ flexible reporting*. These capabilities aim to get a grip of the data and to get insights into various processes. The upper management level or decision makers could employ this reporting system to establish and to monitor the KPIs. Flexible reporting enables people organization to create their own report without going to the IT department to generate the analysis. Through descriptive Analytics, organizations are keen to obtain data from the past to see what happened, what went wrong, what is the state at the moment, for examples: how they will maintain all the gas pipes in the Netherland, how much gas is flowing to particular tubes, where to find available gas now, what is the trend analysis to check on the cash flows, assets or what is the expected profit per share, etc.

However, the Analytical capabilities organizations desire to achieve are not merely involving different type of reporting but also how the organization governs and manage the data. Various processes within the organizations need to be identified correctly and controlled formally through data governance. This is often the case that organizations are unconscious about. More of this topic is covered in the discussion of refined ADOPT-model.

Predictive Analytics

In the term of predictive Analytics, organizations typically desire to foresee the future and to have guidance to take further steps. *Predictive monitoring* is applied for the purpose of equipment maintenance in a semiconductor company. The performance status is indicated with the parameters generated by the machines. Based on these values, possibilities on machine failure can be informed up front when the parameter's value exceeds certain normal boundaries. For instance, the machine might fail within one or two days and they can prepare the entire logistics in advance, e.g. to get the fuel ready in place, and get the parts necessary to repair the machine. Without the prediction, if a machine suddenly breaks down during a production cycle, they must throw away all materials used. The improvement by predictive monitoring can be 1-2% of the uptimes, and save their cost of millions euros as well as their production time.

Process optimization can be carried out to optimize the entire business processing by unifying or standardizing certain process(es) to be executed more efficiently. A transportation company has optimized the network to increase the sales and to deliver better service (i.e. on-time schedule).

Organizations such as insurance companies and a utility company often apply predictive Analytics to define the *best pricing margin* for the company or the fraud detection through analytical or mathematical modeling. For underwriting department, predictive Analytics enable them to calculate the best prediction on the risk of certain event that might happen, predict the highest claim that will be made, or how many more claims will be requested despite the time of occurrence of the event. Hence the premium pricing can be optimized based on those calculations.

6.2.3 Major Analytics Vendors

In the past few years, the market has been experiencing a number of consolidations of different Analytics vendors. Few dominant players in Analytics market have acquired smaller players with substantial technology development. Several key selling points that were shared by the consultants and clients concerning different major vendors are described after the presentation of below thematic network in Figure 18.

SAP BW/ BO/ HANA

In the case of descriptive Analytics, the majority of the consultants consider *SAP* as the major Analytics vendor. Business Object (BO) was a significant former stand-alone organization, which was acquired by SAP a few years ago. SAP BO provides tools application for dashboarding, static- and ad-hoc reporting. SAP is imposing more effort in developing its technology to improve the statistical software and to compete with other predictive Analytics vendors in the market. Not long ago, SAP launched its predictive analysis tool, SAP HANA which is an in-memory technology. Thus far they have made great improvements in the sense of analytical capabilities, although they are still at the development phase at the moment. Moreover, SAP BO has a considerably broad spectrum in the sense of integration compatibility with other underlying systems. On the top of that, SAP is a very large vendor with a high market share as well. However the typical downside lies on the functionality that is often too straightforward for operational or descriptive reporting, and the interface appears to be outdated or is not user- friendly.

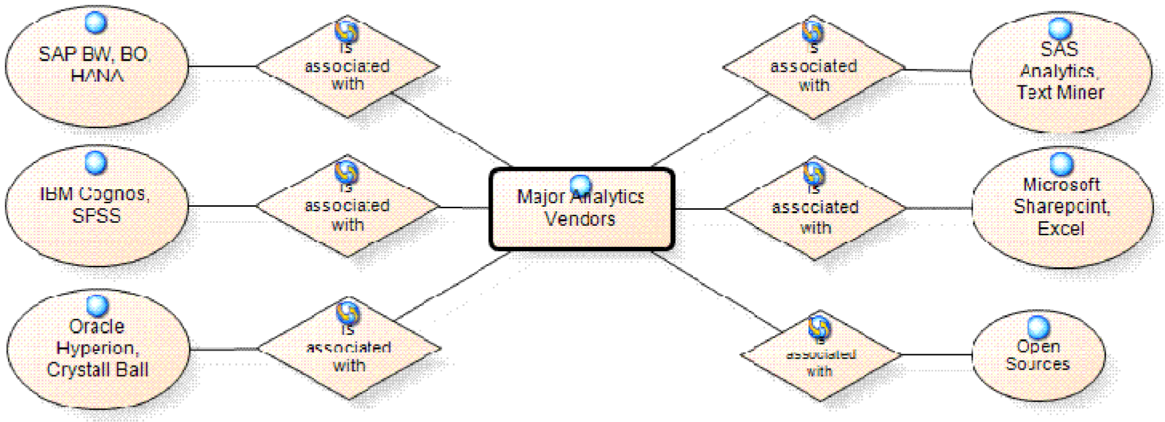

Figure 18. Thematic network for major Analytics vendors

SAS Analytics/ Text Miner

SAS Analytics is typically considered to be a significant Analytics vendor for predictive Analytics. Its main selling points should be its broad functionalities and its nice graphical user interface. SAS offers quite diversified comprehensive mathematical modeling which was very well-tested and the outcome is a reliable as well. No function code is necessary; users could just build their model by utilizing available solutions. SAS provides also BI capabilities with a distributed computing and ETL tools on analytical database. Hence SAS offers very powerful analytical solutions with a considerably high price and the system integration is not always compelling for a hybrid solution. Several organizations from the banking and insurance sector opt for SAS Analytics to carry out risk calculation in their Risk Management, or from the retailers where they often need to carry out very detailed calculations on the demand stock around what they are selling or based on their replenishment stock. These solutions are considered more as pocket solutions which is aimed to a very specific functional unit, rather than as an enterprise solution. This is also why SAS is more recognized as a niche player in Analytics market.

Other Analytics Vendors

Oracle Hyperion is accounted for major descriptive Analytics vendor application that has gained around half of the market share together with SAP BO. In predictive Analytics, SPSS is the runner up in gaining the market share after SAS Analytics. IBM is still improving *SPSS* in facing the struggle with the processing of larger data volume. This is also rather expensive but less than SAS Analytics. *IBM Cognos* and *Microsoft Sharepoint/ Exel* are often selected by companies for the BI market. Microsoft is gaining more of the market share due to its user-friendliness tools. In addition, other low-cost predictive Analytics tools are also available from *open sources.* For example, R is a data analysis software that requires the users to understand the programming language. Users might need to learn programming language, syntaxes, its functions, and have to make their own analytical modeling. Hence, the software has no fancy user graphical interface and is not user-friendly. Other example is Kayako, which is a help desk software tool to support a functional unit to register tickets from the merchant partner and to monitor them.

6.2.4 Vendor Selection Factors

In most cases, organizations undergo a selection procedure to choose the Analytics vendor application(s) that fits best their system architecture. The specialized and/or mainstream vendors can be invited to show the use cases or demos of their solutions, which this is considered as quite an expensive selection process. Solely or together with a third party e.g. consulting company, the organization can exercise and analyze their potential application. Subsequently they can select the best-fit application(s) to their needs and requirements. The client- and consultant respondents were enquired for the key factors how an organization selects their specific vendor Analytics application. The network presentation depicted in Figure 19 shows different validity levels of answers that were provided by the respondents. It is important to note that the bigger ellipse-shaped nodes on the left side of the figure represent themes that emerged from more than one respondent (minimum of two different sources of respondents). In contrast to that, the themes captured in the smaller ellipse-shaped nodes on the right side were emerged only from one specific respondent. Therefore these themes are accounted to have a lower validity level than the nodes on the left side.

Underlying Available System

Before organizations start adopting Analytics, they might have certain system architecture in place. It could be the ERP system, data warehousing, or other systems. The *underlying available system* encompasses the *experience of the users* as well as any *policy-related contracts* with existing vendor. Due to embedded way of working or good experience of the users with the existing system, the organization might think twice to put radical change to their people for example due to new user graphical interface or different functionalities. The consequences could be that they need to re-educate a number of developers, engineers, analysts, etc., and it might evoke people resistance to the new system. Different than that, some organizations might have a long relationship or contracts with (a) particular vendor(s). These organizations will stay loyal to their existing vendor unless that the vendor does not have the solution the organization seeks for, "unless policy". However when an organization is already using certain module from a vendor, they tend to expand their system with existing vendor as there is a lot chunk of data or information that needs to be processed or migrated to the new system. Problems are potentially to be occurred with extracting and transforming data. This is why organizations, especially from their IT department, often choose standardization above hybrid solution where they need to handle thousand different tools from different vendors at the same time.

Adoption Costs

For some organizations, costs might not always be the decisive factor in selecting vendor solution. However, almost all questioned respondents accounted the total adoption costs of Analytics solution to be one of the selection criteria for organization in selecting the best-fit vendor application. The total adoption costs imply such as the implementation cost, licenses cost, integration cost, maintenance cost, etc. The switching cost can also be accounted here as this triggers a higher implementation cost for organization that desire to change their technological landscape. The licenses from different applications included in a software package are usually cheaper than individual purchase. This could also be more appealing for organization to purchase a software suite and utilize the applications included in that package.

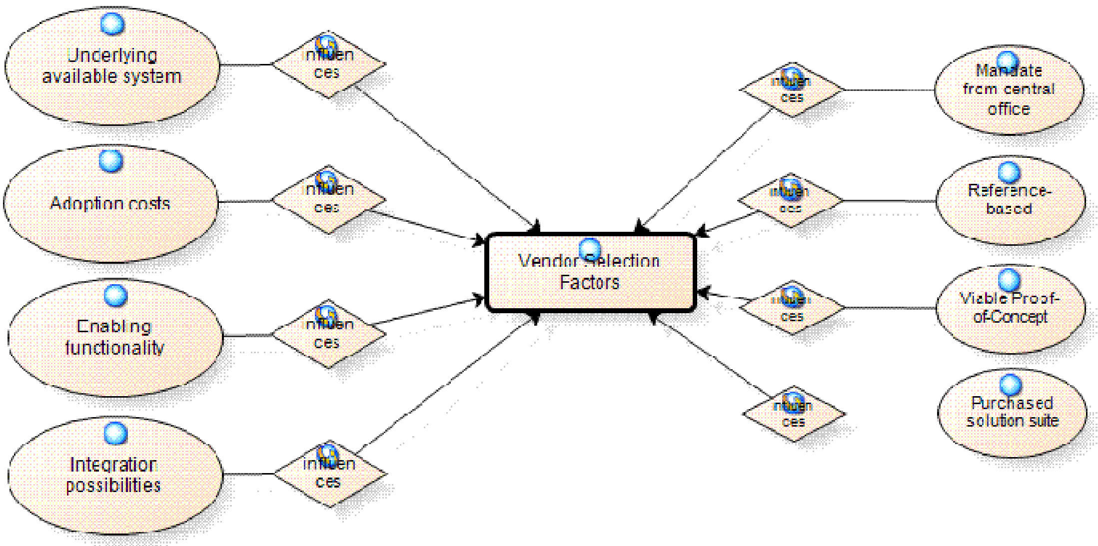

Figure 19. Thematic network of vendor selection factors

Enabling Functionality

The tool selection should be based on the business requirements. This means depending on which analytical capabilities the organization wishes to have, the selected vendor application must provide the functionalities that will enable the organization to achieve their goals. For example, an asset management and pension provider company does not have one particular vendor application but has an existing diverse technological landscape. They have the necessity to employ a very specific tool that is only developed for investment management purposes. At the end they tend to look more towards specialized system from the niche market in that area, rather than a generic application. However, sometimes the organization considers the number of functionalities the application can offer as their selection criteria as well.

Integration Possibilities

As just mentioned earlier, problems in migrating data might potentially occur when the new application is adopted from another vendor than the underlying system. For some cases, the organization really needs to opt for a hybrid solution since their existing vendor of the rest of the system does not provide the solution they seek for. The compatibility of the potential application becomes very prominent to be integrated in the existing system architecture as they not always have all the extraction logic to integrate the system.

Other vendor selection criteria

Typically for multinational organizations, they have standardization for their branches around the globe. If this is the case, the local branches might not have the autonomy to select their Analytics vendor application and thus typically get *mandate from the central office* to apply a particular solution from the contracted vendor. Different than not having the autonomy from the central office, sometimes organizations have *purchased a complete package/ suite of solutions* but they are not aware of all applications included in the package because they did not need certain applications at the time of purchasing. Now they basically have what they need 'in-house' already, they do not have to decide on selecting another solution. Organizations often require a *Proof-of-Concept (PoC)* as well as the potential added value to be presented to them. Based on this, they could decide the adoption of that solution in larger case(s) or even enterprise-wide. In addition, when an organization involves a third-party or a consulting entity they might select a vendor application *based on reference*. However it is notably recommended to involve an independent consulting entity than the offering vendor itself to avoid any biases.

6.2.5 Typical Traits of Organizations Considering Analytics Adoption

Organizations that have adopted Analytics are recognized to hold common characteristics attached on them. Figure 20 depicts client- and consultant respondents' reasoning in identifying typical traits of organizations that have adopted Analytics or are interested in adopting Analytics. Similar to previous presentation of the thematic network, on the left side of the figure with bigger ellipse-shaped nodes are themes that were emerged from more than one respondent. In contrary, on the right side with smaller nodes were mentioned only by single respondent.

It is notable that the majority of the respondents have identified these organizations as *innovative organizations* that are continuously seeking for novelty in what and where they operate their business. This can be in increasing the number of production, improving the process efficiency, generating more profit, becoming more agile organization, or improving customer/ clients services. This type of organization is often associated with owning highly-education or analytical people, thriving as the leading company in employing new materials, products, thoughts, tools, etc.

Banking, insurance, and other organizations with financial departments are technically often applying Analytics due to government regulations, which require certain standard reporting. These types of organizations must *comply with the regulations* in order to execute their businesses. This is also often the reason that they have already good quality of data stored in their database, and therefore they are able to adopt or extend their Analytics capabilities promptly. For example: Basel II reporting is a standard financial report that incorporates comprehensive analytical computation, which is required by the government otherwise that company has to compensate for a penalty. The computation is carried out to evaluate the market condition, to calculate how much risks have been involved, and also external regulations need to be taken into account.

Analytics applications which organizations choose to be adopted often depend on their *primary business*. For finance and bank insurance companies, they do need risk assessment application. Likewise with banking and insurance companies, they must not merely comply with the regulations but also to know what to act when things go terribly wrong as in the sense of detecting frauds and controlling insurance claim. This is known as fraud detection. Hence, the characteristic attached to organizations that are interested in Analytics is usually associated with the industry type wherein the organization is doing their core business. For example a bank in mitigating their risks based on customer segmentation, Analytics application for risk management purpose is essential for them to carry out their primary business. Another example of a utility company; they need to collect a lot of data and to monitor electrical grids to be stable in the future. Also to foresee the electricity supply-demands in the so-called smart-grid concept, hence Analytics is an aid to support their business.

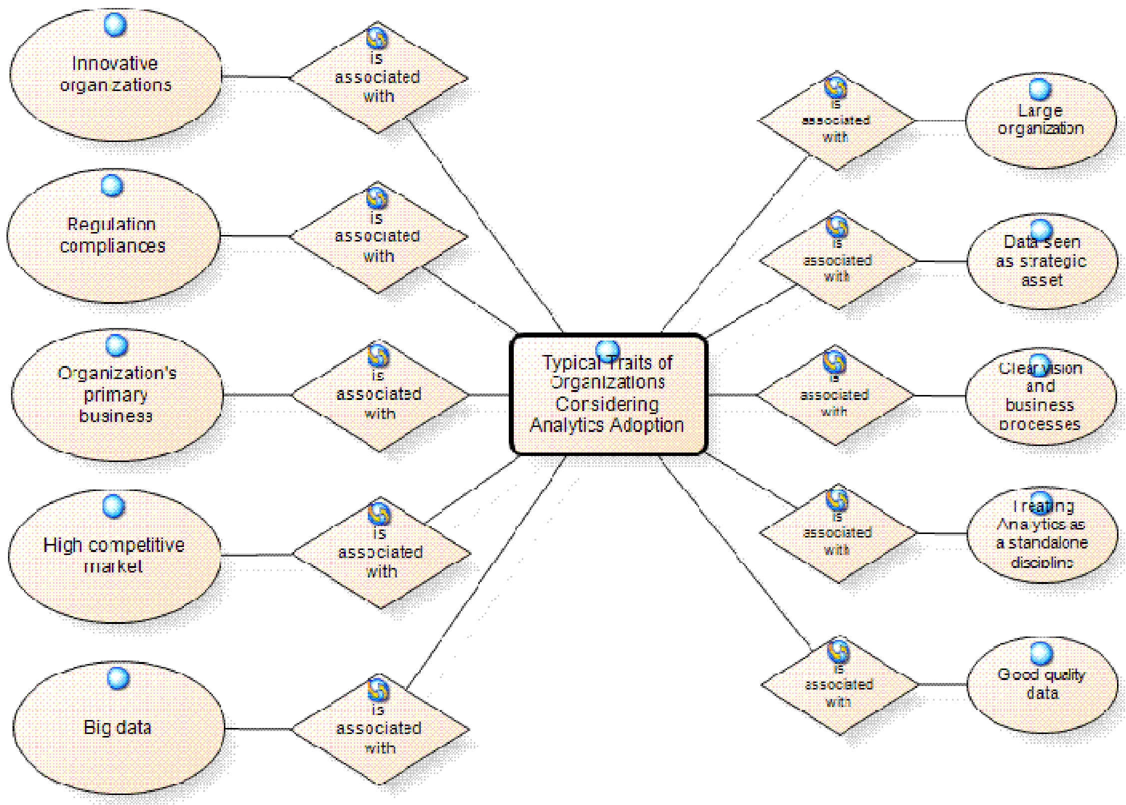

Figure 20. Thematic network of Analytics organizations' typical traits

Another trait of Analytics organizations is recognized by their high-performing culture in thinking more strategically and perceiving data as their strategic asset for their fact-based decisions. In many cases, these organizations are present in a *highly competitive market.* The insurance companies typically deal with a chunk of data that is also considered as their remarkable strategic asset. Due to this fact they need Analytics to stay at least at the same pace as the other peers.

As multinational organizations deal with incredibly *huge of data* flows and often have the necessity to integrate their data globally, Analytics can assist them in managing their data and generating valuable insights of their global figures. In many cases, big data is associated with *large organizations* which have the necessity to apply Analytics in achieving their business goals.

Other characteristics emerged were the fact that those organizations usually have a *clear corporate vision and their business processes*, and they also own *a good quality of data*. It creates a notion that the organizations are often seen as more industrialized, professional organizations that *treat Analytics as a standalone discipline*. This discipline has their own team, which has values on its own and is seen as a competency that needs to be managed and developed. In prior to this, Analytics was seen as the part of a lot of ERP projects, just because these projects need some reporting system. However, more organizations today are creating specific department handling this topic.

6.3 Adoption Process Evaluation

The execution of Analytics adoption entails several concerns that can restrain the adoption process. This section enlightens these concerns as challenges in different perspectives, namely in terms of Structure, Process, People, and Technology. The adoption challenges are described subsequently starting from Section 6.3.1 to Section 6.3.4. In addition, the most critical adoption phases are identified based upon consultants' experience in this area of study. These themes are elaborated in Section 6.3.5.

6.3.1 Perceived Adoption Challenges in term of Structure

The challenges during the adoption of Analytics are firstly attempted to be recognized at the organizational structure layer. The thematic network is presented in Figure 21. Still in many cases, decision-making based on gut-feeling has been going on for ages within organizations. Questions are often raised from this type of organizations why they should change their way of making decisions since they have been doing their business for years. It is not surprisingly if these people refuse to accept the new Analytical culture. This challenge is accounted to be one of *the cultural issues* an organization often has to face. At first glance, the organization must have sponsorship from the top level management, but along the way they really need to have the ability to manage the people and to involve a lot of Change Management elements. However Analytics must be accepted by the people and organizational culture. This cultural issue is also partly related to people organization. This kind of issue especially appears in organizations that have been doing their business for generations, e.g. transportation company.

As just mentioned in previous paragraph, sponsorship from the top level management is crucial in the adoption of Analytics. Despite of this fact, if sponsorship *cannot be translated to a form of mandate* to the operational level then the adoption process can be hindered when people are resistant to accept the transition. For example when the organization intends to train or give workshops to the employee, but they refuse to follow those trainings/ workshops due to no interest or some other reasons. The organizational top or the leadership should give mandate or motivate their employees to accomplish those trainings/ workshops. If there is no mandate from the top down to the bottom level, transforming organizational structure could be very challenging.

The third key challenge perceived by the respondents is still related with the sponsorship the organization must hold to assure the adoption process going on with ease. The organization needs not only support from the upper level, rather from all level of the organization. This *organizational buy-in* must embrace the shareholders to realize the added value of Analytics to the business and how this can elevate company's profitability. People organization must "buy-in" to the ownership of certain processes, group of people, and technology. Accordingly the organizational sponsorship is needed upfront, because the formation of Analytical capabilities will cost time, money, and effort. Once the organization has decided to define certain objectives and requirements, there must be already some kind of sponsorship to undertake the initial assessment in their organization. Without this sponsorship in the transition process, no one will take a part of the responsibility to realize the transformation, or worse, when things go wrong.

Once the organizational buy-in is gained from the stakeholders of the organization, it is remarkably important to keep *managing their expectation* in the relationship with those stakeholders. This can be done by informing stakeholders at which phase of adoption they are currently, what will be delivered, what they can achieve, or what is not viable. If the adoption planning is not viable, over-expectation or unpleasant surprises might be emerged and the adoption process can be hindered.

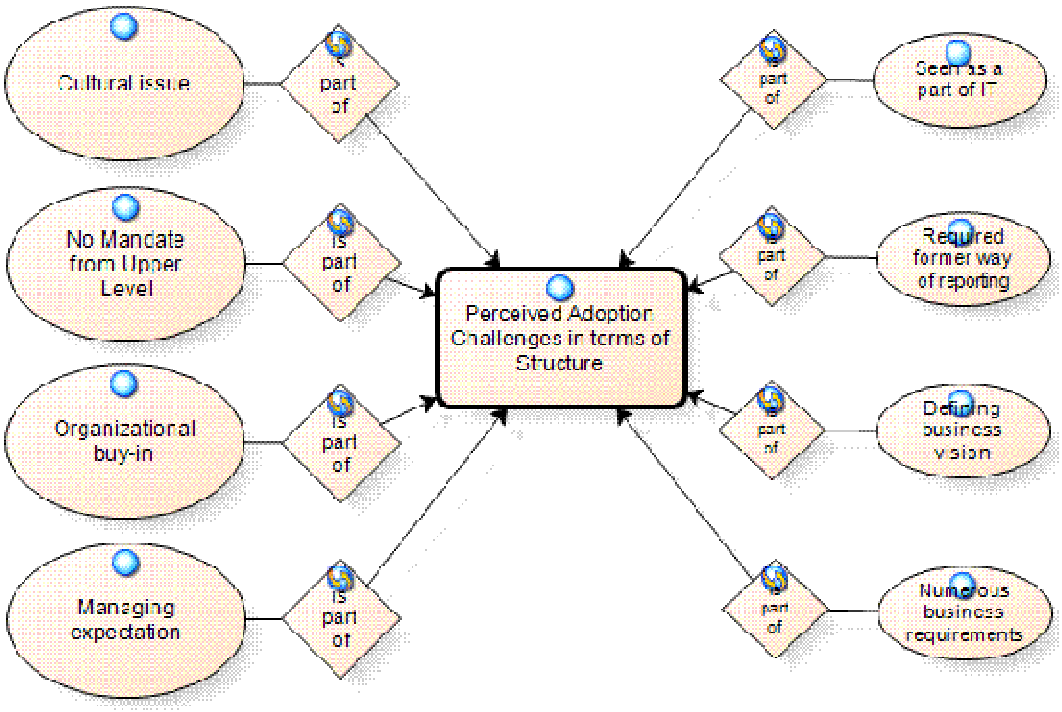

Figure 21. Thematic network of perceived challenges in organizational Structure

Peripheral challenges perceived in transforming the organizational structure towards Analytics are depicted in the Figure 21 on the right side nodes. Analytics solutions are often *seen merely as a part of IT,* not as a business function. In many cases, people that have more understanding about the business or people from the business side are not even included in the adoption process of Analytics. Despite where the Analytics initiatives are originated (business- or IT side), Analytics will never be able to serve the business if no substantial knowledge about the business is available. Nevertheless, the entire level of organization must collaborate in employing the new Analytics system when it is implemented. The end-users must adapt to the new way of working, and the upper level management where they need to report to *must not require for the former way of reporting*. The transformation must take place mutually, ones who provide the information and too who need the information. However, some organizations still have *vague definition of their own vision* and therefore they have the difficulties in defining what they want to achieve. As opposed to this, there are organizations that *have too many requirements* in which they cannot prioritize their goals. These organizations need to be more selective and be realistic.

6.3.2 Perceived Adoption Challenges in term of Process

As the championship of various processes needs to be assigned to the process owners, these *owners are accountable for the transition* to be promptly carried out. Although these ownerships are stated on paper and agreed by the stakeholders, the concern lies on the actual execution or realization of what have been defined earlier. These owners must act upon the new defined processes and take the responsibilities of their ownership(s). However sometimes unexpected circumstances might occur during the transition which are above their supremacy.

Next, the following challenge was recognized by more than half of the respondents to be the most intricate component during the Define-phase. Setting up a good business case with an accurate estimation of related costs and potential benefits is often very difficult to carry out, especially at the very early phase of the adoption as well as when the processes are too complex. The main concerns are thus to *create a proper business case* and to communicate the real business value to the shareholders so the transition project can get adequate support.

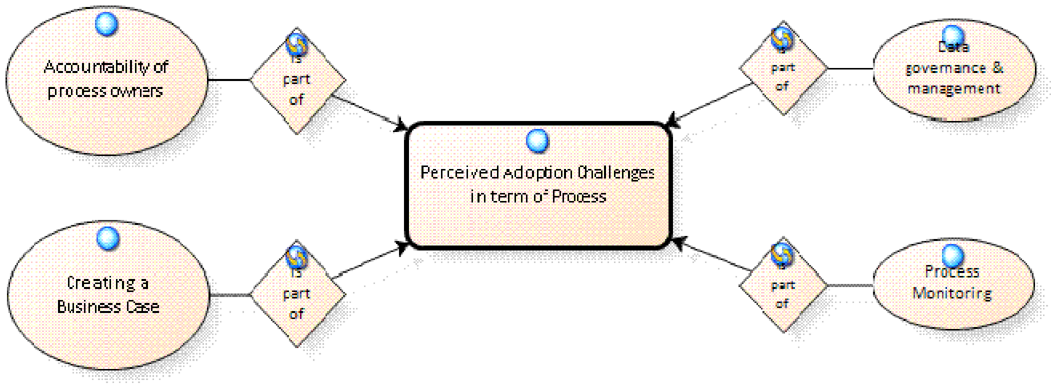

Figure 22. Thematic network of perceived challenges in organizational Processes

Other challenges perceived in the sense of Process are how *proper data governance and management* in the organization could take place, and how to *keep the transition process in track*. In many cases, organizations sometimes overlook that they need to properly govern and manage their data in prior before they can start adopting Analytics despite when the process owner does not feed their own database. Moreover, the right tooling is often difficult to be defined and selected when the upper level management within data governance has no insights in the technical requirements. Their priority might be different than the engineers or technicians working in the operational level. For example, the managers want to keep good relationship with a certain vendor but technically other vendor offers a better Analytic solution, which was more preferred by the statistician. However when the transition process is undertaken, monitoring the process to "keep the eye on the ball" can be very challenging. This can be due to the involvement of numerous stakeholders within various processes that are sensitive to unnecessary alterations. Therefore the key issues are imperative to be identified early during the process and let everyone adhere to those key issues.

6.3.3 Perceived Adoption Challenges in term of People

The majority of all respondents acknowledged the difficulties in acquiring people with the prerequisite capabilities as well as *getting the right people* early *on board*. The labor market wherein qualified people are needed to create analytical capability in a company is very much limited. However organizations could involve a third party for filling in interim roles until they have their own people in place, for instance hiring workforce from a consulting company. Another concern relating to this challenge is that organizations sometimes do not involve business people to specify their business needs. The IT people are often enforced to define the business requirements that might deviate from the real business perspective. Consequently those requirements appear to be more as technical requirements and Analytics added values seem to be hard to realize.

The support on Analytics adoption should not merely obtained from the upper level management, but vertically from the top to the bottom at the operational level as well. Organizations need people to execute the transition project and to work in the project team, in which people sometimes hesitate to join in. People might get new roles and be assigned for new tasks. When people do not understand what they need to do, they might be reluctant to carry out the tasks. Hence, people need to be engaged early from the beginning of the project to anticipate that they know what the organization is trying to achieve, how they must react and nevertheless with clear goals and requirements. This way *the organizational buy-in* is potentially achievable.

As the following challenge has been discussed previously regarding the cultural issue perceived in organizational Structure, this is indeed partly relating to how well Analytics can be accepted by the people organization. Sometimes when the entire new system has been implemented, people can be very reluctant to utilize the new tools because they do not understand or not adequately (re)-educated. They tend to keep their previous way of working for example because they are used to work in an Excel with macro sheets, and refuse to work in the new enterprise portal with fancy dashboard etc. This way of working is completely embedded individually that the organization has hardly a grip on it.

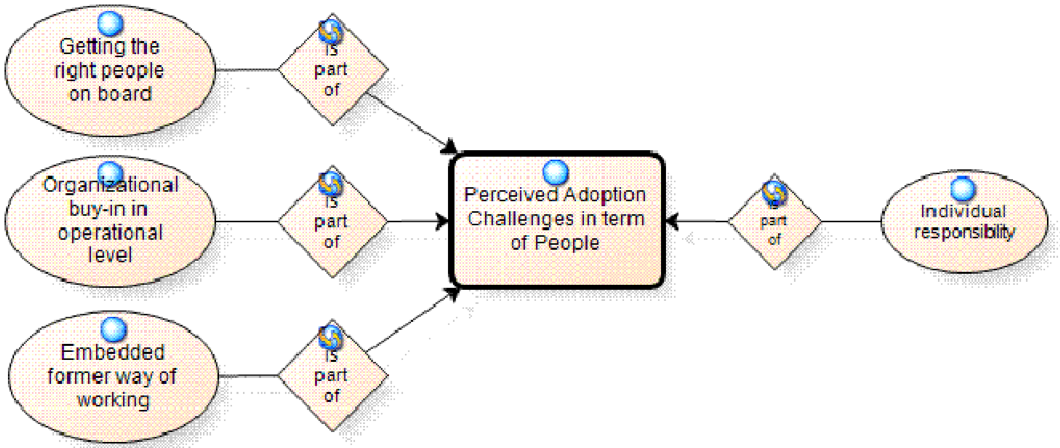

Figure 23. Thematic network of perceived challenges in People organization

While people are assigned to be accountable for specific role(s), they are expected to hold the ownership of certain tasks and must act upon it. People get assigned for certain role(s) on paper but they do different things in the real situation. So getting these people to take up their *individual responsibility* they are assigned for is pretty much challenging. However from another perspective, if these people are not well- prepared before they start using the new system or they are not sufficiently aligned with the rest, people might feel as if they are drowned in the new situation without further explanation. They might feel trapped if they do not know the way out. That is why it is extremely important not to underestimate the end-users, which can terminate the adoption process.

6.3.4 Perceived Adoption Challenges in term of Technology

At first, it is very crucial to have a *good quality of data* before an organization starts to apply Analytics solutions. Organizations that are aware of the importance of data quality typically have much better data quality than organizations that are not aware of it. However more organizations acknowledge this data issue, although very often they have good quality of data in place already because they must comply with government's regulations. Organizations must understand that the availability of good data is a key factor to be able to calculate predictions. An example from a grid company that still have troubles in capturing valuable data to be used as data sets for generating forecasting. That is why the technical objectives must include the specification of how clean the data must be or what kind of data is important to be captured, etc.

Organizations that are not very used to handle complex processes and to have data governance, it could be cumbersome to establish *data ownership* to be appointed to particular owners. This concern is certainly involving people organization. People might be not accustomed to govern the data and make decision based upon the data. The organization must be careful in recognizing the owners that understand their business and can take up the responsibility. The business availability must present in the ownership of the enterprise architecture. These process owners need to fill in their own database, which data is accounted as valuable to support the business, what are the KPIs, what kind of insights the business is looking for, etc.

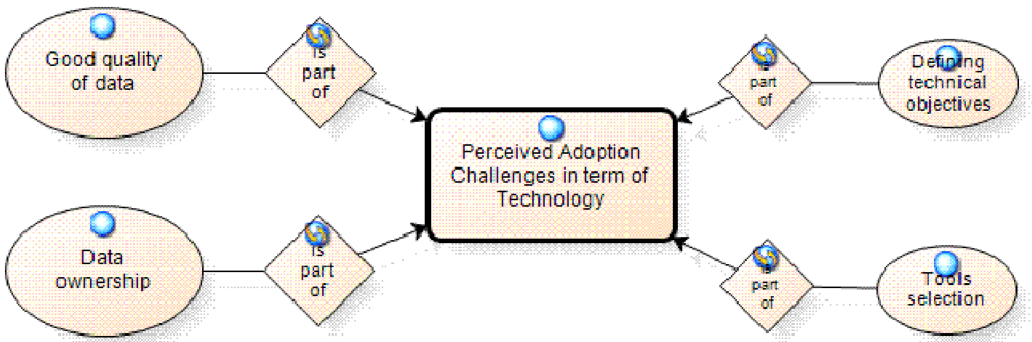

Figure 24. Thematic network of perceived challenges in term of Technology

One of the consultant-respondents believes that the technical objectives are critically eminent in selecting the right Analytics application and at the same time these objectives must be aligned with the business requirements. If the organization has wrongly *defined the technical objectives* and accordingly not selected the right tool(s), then they might have to start all over again (although this is hardly ever happened according the respondent) or might be completely failed in applying Analytics. On one hand *the tool(s) selection* is indeed based on the technical objectives, but on the other hand it also depends on the upfront assessment of the current system architecture. The business problems must be translated to the technology option through for instance, the ERP system. The organization needs to question themselves whether this system is really going to work and can be integrated with other systems in the company or solution architecture. The system assessment could lead to which package should be employed, which version of software should be used, when a certain piece of software should be adopted, or by checking the technical components whether they will work well together or whether the system is mature enough to be implemented is necessary to be carried out correctly.

6.3.5 Most Critical Adoption Phases

Diverse adoption challenges were just elaborated through four different organizational perspectives in previous sections. While those sections accounted the data analysis from all respondents, this section attempts to present the most critical adoption phases reflected based upon consultant's experience during the entire Analytics adoption process in quantitative figures. Clients' responses were not accounted in following figures due to their limitation in experiencing throughout the adoption process. The most critical adoption phases to progress according to the consultants are presented in the pie charts depicted in Figure 25 through Figure 28 in respect to the organizational Structure, Process, People, and Technology consecutively.

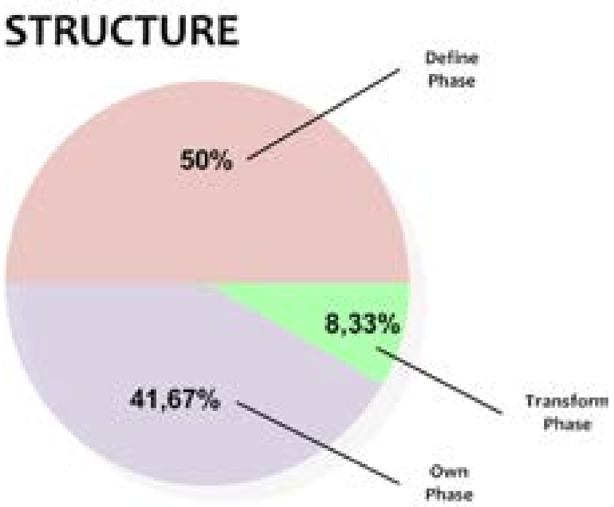

Figure 25. Critical phase in term of Structure

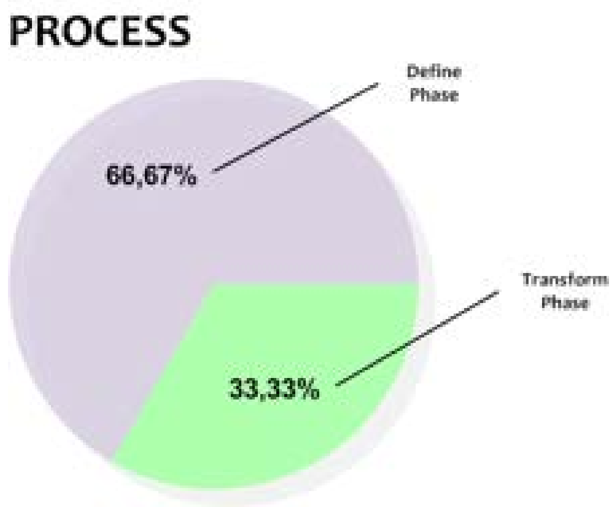

Figure 26. Critical phase in term of Process

STRUCTURE

The half of the respondents agrees that the most critical phase to progress is during the *Define-phase*. A clearly defined business vision and requirements are the 'must-have' component to adopt Analytics promptly. If the business vision and requirements are wrongly or vaguely defined in this phase, all following phases might be halted or they must re-define those things. In contrast to this, sometimes the organization Board has too many business requirements that can also retain the adoption process. This type of organizations must be more selective and focus merely on the key goals.

A slightly above forty percent of the responses conformed that *Own-phase* can be cumbersome to undergo when no sponsorship from the executive level is present (see Figure 25). The business values they can get from Analytics must be tangible and be correctly communicated to the Board of executives on how exactly Analytics can aid them to achieve their goals, rather than only describing what Analytics means. This can be done by bringing those executives up to date concerning Analytics and appointing the real problems which can be solved by Analytics within the business unit. Nevertheless, careful steps must be undertaken to avoid people's expectation becomes inflated.

One respondent considered Transform-phase to be the most troublesome phase in transforming the Structure-element to become more Analytics. In this case the concern lies on shifting the organizational culture to Analytics culture and having this culture rooted in the people organization. Indeed, this is partly relating to the transformation of people organization.

PROCESS

The main concern of two-third of the respondents is to be able to set up a good business case concerning the cost and benefits estimation of particular Analytics solution. After the assessment is carried out in process wise, business gaps can be identified during the *Define-phase* to seek for solutions to encountered problems.

In respect to business process transformation, the target process must stay as much as possible as the existing processes and close to the organizational culture. If the target process does not change drastically, then the *Transform-phase* would not be that tough to undergo but still needs careful steps to take. At least, this is argued by one-third of the respondents with regard to the process transformation (see Figure 26 above).

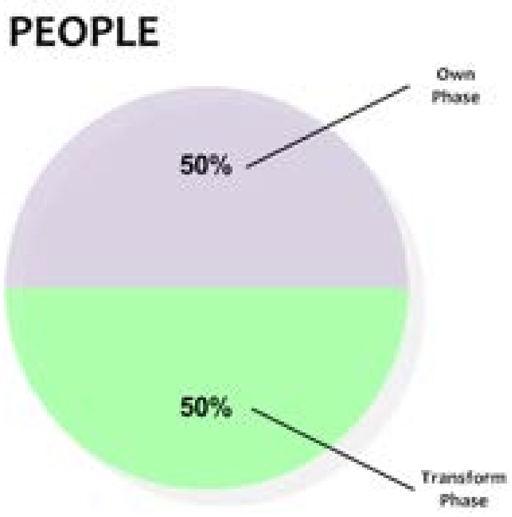

Figure 27. Critical phase in term of People

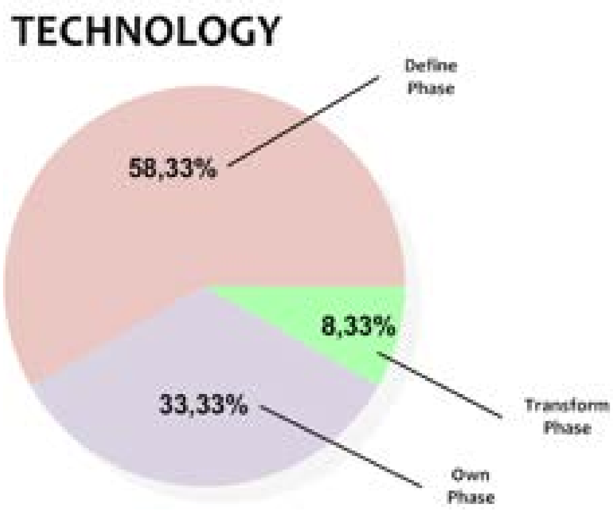

Figure 28. Critical phase in term of Technology

PEOPLE

The pie-chart illustrated in Figure 27 is exactly divided in two equally. So the half of the respondents experienced the cumbersome to endure *Own-phase*, and the other half experienced during the *Transform-phase*. However, getting the right people on board has never been done with ease especially when high requirements must be fulfilled. Afterwards, when the real implementation happens the cultural shift must also take place. People must start to work in a new way which will be the part of their normal business workday. For instance; business people who are good in selling or purchasing, suddenly they have to rely on a new model to make decisions. This can be a major mind shift for a lot of people and sometimes might take years before they are transformed entirely.

TECHNOLOGY

More than the half of respondents contemplated that determining the technical objectives and the tools selection are vitally important during the *Define-phase.* During the vendor selection, the organization usually should decide on their desired adoption terms. However, they might barely know the answer and are often not knowing what they really need, they want to use, how enhanced they wish to implement the new technical solutions, or what is their future state. This phase could be a tedious phase to withstand.

As not surprisingly new, one-third of the respondents still consider data quality to be a concerning issue. Likewise, for the designation of data owners might be cumbersome when Analytics is seen only as a part of IT. No ownership of data is taken up for the business side could endanger the achievement of organization's target capabilities. Business people should always be available for assigning the data ownership during *Own-phase.*

Specifically to transform the technological landscape during the *Transform-phase* appeared to be the most critical phase to endure for one respondent (see Figure 28). Changing the entire system architecture could be very complex to accomplish as well as ensuring the new system to be correctly operated by the end-users. However, this should not be troublesome when the organization have a proper data governance and management in place.

6.4 Verification of ADOPT-Model

During the empirical data collection, diverse feedback, confirmation, and adjustments were received from both client- and consultant respondents. Since the dialogue with the consultant-respondents was emphasized on the evaluation of the conceptual ADOPT-model, not with client-respondents in particular, the verification of initial ADOPT-model was constructed based upon the inputs provided by the consultants. This section elaborates the ramification of all gathered inputs mapped into the initial ADOPT-model (see Figure 14). In the following paragraphs, each of the intersections between the organizational elements and adoption phases will be discussed in more detail encompassing respondents' inputs. The initial ADOPT-model throughout every adoption phases will be partially presented by disjoining each of organizational elements horizontally from other elements to have a better focus on that particular element. However, the complete presentation of refined ADOPT-model can be found in Figure 33.

The understanding of both organizational elements and adoption phases remains the same as described in the initial ADOPT-model. Some of the 'adoption activities' were completed, adjusted, or eliminated from the dotted-line boxes. No drastic adaptation occurred during the refinement of this model, rather better insights and ratifications that underpinned the construction of ADOPT-model. The discussion of verified model starts with the layer of organizational structure in the following paragraphs.

6.4.1 Organizational Structure

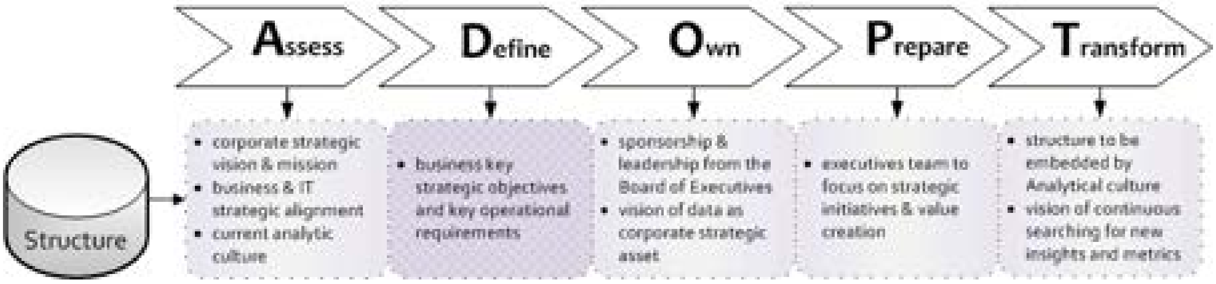

Figure 29. Verified model in organizational Structure

STRUCTURE – ASSESS PHASE

In most cases, organizations usually undergo this assessment phase quite straightforward. The organization's current strategic vision and mission should be evaluated whether those are clearly defined, whether the business-IT strategic alignment is present, and how far the current Analytical initiatives are. Foremost, it is imperatively notable to understand what the organization desires to achieve with its business in particularly and what the rationale behind it is. The assessment can be carried out by reviewing the annual report or other available documents, interviewing the shareholders, senior managers or sponsors, etc. As this organizational element embraces the culture of organization as well, its decision-making culture needs to be evaluated whether facts or intuition is commonly opted as their foundation to make decisions. Any analytical capabilities should also be identified whether its distinctive capability is present in silos or across organization. Accordingly the maturity level(s) of different analytical capabilities could be determined for each of functional levels in the organization. At the end of this phase, the organization could better position itself in term of Analytics maturity level to be the starting point to arrive at their desired maturity level, which is the focus of the next phase.

STRUCTURE – DEFINE PHASE

This phase appears to be the most critical phase in transforming organizational structure according to half of the consultant-respondents. Creating a direction to the future state is very crucial for every organization, but at the same time extremely challenging to accomplish this. The organization needs to define what the business key strategic objectives are and which business key operational requirements are necessary to undertake actions in order to achieve its goals. Transforming the structure of organization happens rather continuously, as they have in a prior the general scoping defined and things should become more concrete as the adoption process goes on. However an organization needs to have a clear view at the beginning in defining what they want to achieve, why, and how they might be able to achieve that. It is important to note that defining organization's operational objectives might need regular iterations as well as learning process to underpin the vigorous steps to take.

STRUCTURE – OWN PHASE

The own-phase has taken its position as the runner-up to be the critical adoption phase in respect to organizational structure. The sponsorship and leadership should be owned especially from the Board of Executives. Potential business values gained from Analytics must be correctly communicated to these sponsors without being to obtrusively. Nevertheless, their expectation must not become inflated, which means managing the expectation of these sponsors needs a careful attention e.g. bring them up-to-date regarding adoption process, fairly inform them what can be achieved and which are not doable, etc. The organization should own a strategic vision that accounts data as their strategic asset and subsequently treat data as central to their business, rather than the process. For instance the upper level management might encourage employees to think about which data they might need or is essential to perform their job better, and to start capturing those valuable data.

STRUCTURE – PREPARE PHASE

In this phase, the organization needs to prepare a group of sponsors encompasses the organization's executives or top level managers to focus on organization's Analytics initiatives and the creation of potential values out of those initiatives. Bringing in these sponsors altogether is often not the concern anymore here, but for them to keep stimulating the organizational people during the transition process and keep communicating the initiatives to the stakeholders could be challenging to accomplish. This group of sponsors is also the one who need to start thinking about the integration in the organization and the one who supposed to facilitate the people to integrate into new Analytics environment easier, e.g. (re-)educate the people, less complex procedure in sharing data, etc. Thus, the Analytics initiatives should be passed down to the rest of the organization by the upper level management applying top-down approach.

STRUCTURE – TRANSFORM PHASE

At the end of the adoption process, the real structural change is taking place. The organization should embed the Analytics culture within the structure of organization, where the decision-making must be based on facts instead of on gut-feelings. Analytics value creation should also create organization's distinctive capabilities. The vision regarding data importance must be expanded to continuously searching for new insights and metrics. Accordingly Analytics is practically rooted in the structure of the organization.

6.4.2 Organizational Process

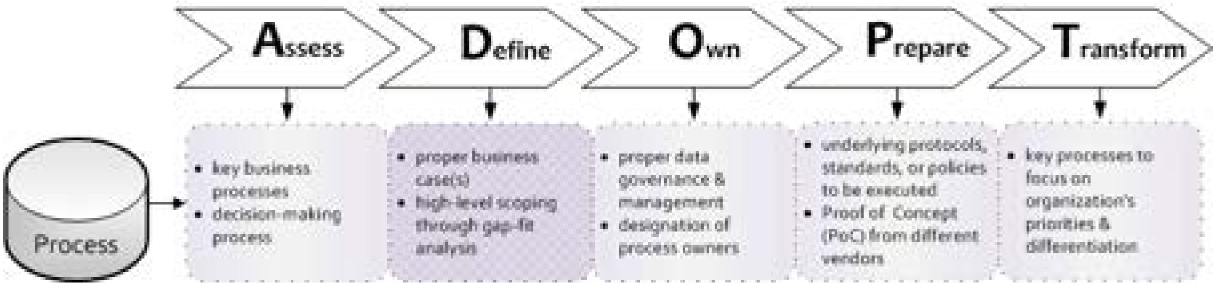

Figure 30. Verified model in organizational Process

PROCESS – ASSESS PHASE

The Analytics adoption within the organizational process starts with the identification of various processes going on in the organization and how they are ready to accommodate Analytics. These processes are evaluated to discover which processes need changes, improvements, or optimization; any overlaps need to be eliminated; or gaps need to be filled in. The latter part is known as gap-fit analysis in which business gaps or problems can be detected to be filled in or solved during the next phase, Define-phase. Moreover, the organization must evaluate how its decision-making policy is (Attride-Stirling)centralized and how Analytics drives the decision making in the organization (on fact-based or intuition-based).

PROCESS – DEFINE PHASE

The real Analytics project is often kicked off by setting up a business case, which might also be reason why the majority of the respondents (nearly 70%) marked this phase to be the most critical phase in transforming the process. After the key processes are identified and the gap-fit analysis is carried out, problems and gaps can be discovered and accordingly adoption areas can be scoped. Hence the estimation of the potential benefits that are doable to achieve with the costs entailed can be made with respect to the precondition of people-element and technology-element that are derived from the predefined new processes. Utterly, the organization needs to define their future state of what they want to achieve and how to accomplish that by measuring certain parameter of their processes so they can grade their performance. This can be done by defining their Key Performance Indicators. Therefore they can set their success when their target goals are achieved.

PROCESS – OWN PHASE

Before the new processes can be transformed, an organization must own a proper data governance and management. Both involve more in the sense of getting the new business processes to be carried out by the prerequisite people by means of the enabling technology rather than merely concerning the technology itself. Data management is about how the organization handles the data, and how the work flows are going on. These work flows are usually stored in the system which is basically putting various processes next to the technology subsequently. Likewise, the data governance is more how to structure the people to own the right process and to be accountable for their processes. So here is where the designation of process owners occurs.

PROCESS – PREPARE PHASE

During this phase, the underlying protocols, standards, or policies must be prepared to be executed across organization e.g. setting up requirements to submit standard reports, where to submit the reports, how the navigational paths are settled to access Analytics application, etc. Organizations often request for the Proof-of-Concept(s) from several offering vendors to get more perceptions of the particular application whether it really fits into the existing system and sometimes to create more awareness or buy-in from the organization. The realization of PoC is partially depending on the technological part as the implemented software or application is the enabler to optimize the process or to carry out analytical calculation concerning the process.

PROCESS – TRANSFORM PHASE

The challenge in the process component is mainly due to time-consuming efforts to make the new way of working to be really embedded in the process improvement. The multi-actors network that is being involved could be very complex and large which may lead to the confusion in the transition phase. This might cost a lot of time and effort to have smooth flows of process. This is also greatly related to people who often require for time to be able to really understand the alteration of a single process of improvement. This is remarkably important that organizations must focus on their

Analytics priorities and organization's focus of differentiation when transforming their key processes to be more analytical.

6.4.3 Organizational People

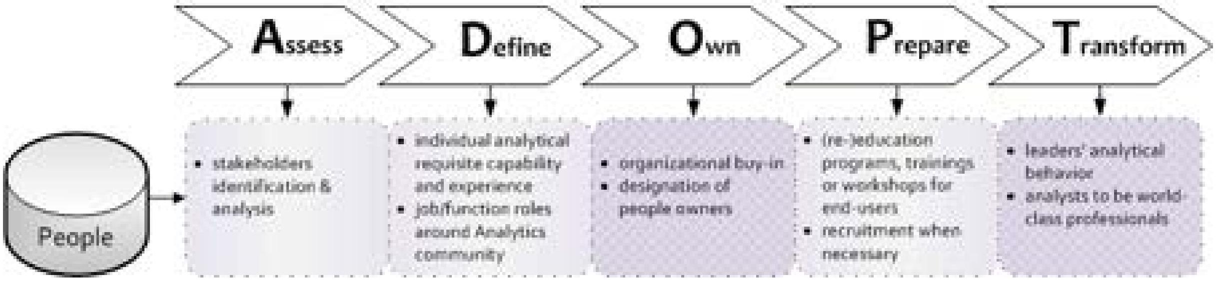

Figure 31. Verified model in organizational People

PEOPLE – ASSESS PHASE

Almost all of the respondents, without being questioned specifically, mentioned that the organizational people are the foremost crucial component than those three others. But at the same time the most cumbersome element to handle. First thing to perform is to identify the relevant stakeholders in the organizational network, and to analyze their roles and relationships among others. As being part of the gap-fit analysis, vacant roles can be discovered and accordingly the prerequisite individual analytical capabilities and experience can be defined during the subsequent phase. It is critical to identify the stakeholders correctly because this is also the phase where people buy-in and sponsorship can potentially be attained.

PEOPLE – DEFINE PHASE

As aforementioned, the definition of the requisite individual analytical capability and experience can be specified based on the gap-fit analysis. In many cases, it is cumbersome to get the right people with requisite skills on board. The type of people required within Analytics organization is typically people that have a good common sense with analytical capability. For Analytics projects, the organization requires people with heavy and high level statistical calculations to be involved in the project. This is often very difficult to assign certain roles to eligible people with high-skilled qualification. Also these people are required to have the knowledge about the technology and its functionalities, as well as to have a good communication skill to be able to convey notable insights to the organization's decision makers.

PEOPLE – OWN PHASE

As the buy-in and sponsorship from the upper level management is essential to gain at the beginning in order to accelerate the adoption process, the organizational buy-in is decisively important to succeed at the end of the transformation process. This is particularly due to the end-users who will operate and use the new system. The responsibility in assuring the smooth transition process of the human resources can be assigned to an individual as well, e.g. to the head of HR department or the team manager. Likewise for the ownership of certain process(es) and technology must be assigned to the accountable owners to ensure that the predefined vision is carried out correctly. Examples of a few roles: IPO (Information Process Owner), he/she owns the process or the path in which the data flows and DVO (Data Value Owner), he/she owns the value over specific data object across multiple sources.

PEOPLE – PREPARE PHASE

After the role vacancies are identified, the organization could search for the new Analytics talents either through internal- or external recruiting. For internals, they can be reeducated through study programs, workshops, or trainings. As the organizational buy-in should be attained in previous phase, these new Analytics talents (including the end-user) are expected to commit themselves to follow the given courses, to attend the meetings, etc. because they also have the feeling being involved in the adoption process and support the initiative to be succeeded. In some cases, the top-down approach, as discussed earlier in the organizational structure during the *Prepare phase*, helps facilitating and accelerating this phase as well as the integration between different levels of functional areas.

PEOPLE – TRANSFORM PHASE

When the organization does not have the roles and responsibilities defined clearly, then it will be very challenging for the organizational people to be engaged in transforming the organization. People should not only be committed around the execution of the adoption as just mentioned previously, e.g. attend the meetings, finalize trainings, etc., but they should also be accountable for their roles and responsibilities on paper to practically perform their tasks. Accordingly, the leaders could transform their behavior to be more analytically and be more passionate for analytical competition. Likewise, the analytical amateurs could be the world-class professional analysts. Anyhow, analytical culture is greatly part of organizational people as well. The analytical culture, e.g. fact-based decision making, will be embedded in the way of making decisions in the organization. However, people who have been working in the organization for quite some times might be reluctant to accept the new situation. Due to this fact, the transformation phase is flagged by the respondents to be as critical as owning the qualified people on board which is performed during *Own-phase.*

6.4.4 Organizational Technology

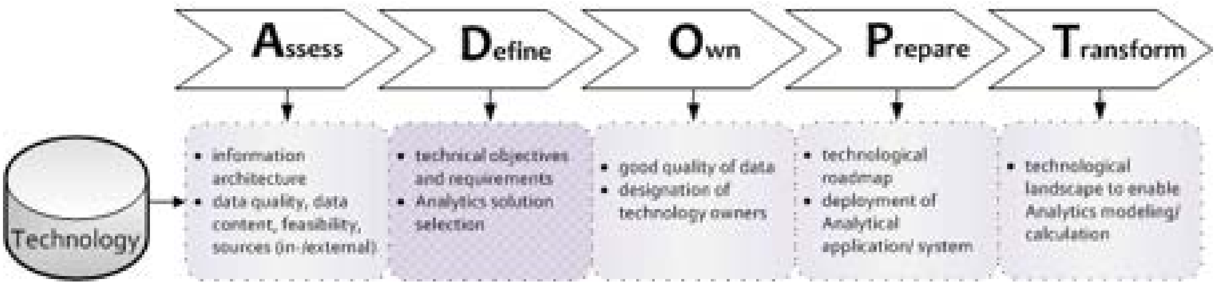

Figure 32. Verified model in organizational Technology

TECHNOLOGY – ASSESS PHASE

In the first place, the current technological landscape must be evaluated underlining how the information architecture is built up, how the performance of ETL layer is, their data services, reporting, etc. The data readiness should be reviewed with respect to the data quality, data content, data sources, etc. Which Analytics capabilities can be supported by the existing system and how compatible is the existing system to be integrated or extended with the new system. Hence all questions raised here could be answer to define the organization's maturity level concerning the technology.

TECHNOLOGY – DEFINE PHASE

Based on previously defined business vision, the technical objectives and requirements must be defined accordingly. The business and IT strategic alignment is crucial to create since the technology is the enabler to solve the business problems. Without this alignment, the questions raised on the side of the business cannot be answered correctly from the technology side, hence the business value is impossible to realize. In addition, when the business objectives and requirements are not thoroughly understood, the tools might be mistakenly selected. The solution architecture is basically created based on the business requirements, which is some kind of the blue print for the technical solution in meeting the business requirements. So the assessment can take place to find the gaps between the executions of the solution and the real situation where business requirements are attempted to be met. Due to these facts, more than half of the respondents accounted this phase to be the most critical phase here. If this phase is failed to be executed properly, the organization might have to reassess and redefine the key issues all over again.

TECHNOLOGY – OWN PHASE

The availability of good quality data is the key factor to create proper predictions and produce adequate calculation. Therefore the technical objectives could include how clean the data must be, what kind of data is necessary to capture, etc. Next is to appoint the data owners. Organizations that are not used to have data governance and management would be difficult to establish this kind of data ownership. Moreover, the common mistake made is that the data owners are originated from the IT people, instead of from the business side. Therefore the designation of the data ownerships should pertain to the availability from the business side.

TECHNOLOGY – PREPARE PHASE

The Analytical environment in the sense of technology can be prepared by setting up the technological roadmap or the solution architecture. The roadmap should be based upon the business strategic objectives that will guide the deployment of the analytical application. Any technical issues should not restrain the adoption process as long as the organization is accommodated with technical troubleshooters. Referring back to the *Prepare-phase* concerning the organizational process, the execution of the Proof-of-Concept can be accounted more as the technology importance. Based on the new processes defined, the technology selection is selected to be deployed in the organization but in smaller case(s). Later the technology is evaluated whether the selected application could indeed meet the business requirements.

TECHNOLOGY – TRANSFORM PHASE

The last but not least, the transformation of the technology landscape is essentially important to enable the organization to perform their business more in the sense of Analytics. All the requisite system should be correctly in place and ready to be operated by the end-users. When the system does not operate as it should be, no insights can be extracted out of the database, and no decision makers could make decisions based on fact. At the end, the creation of business value is failed to achieve. Though the *Technology-element* is often considered as the least critical organizational element, but it still holds the crucial role as the means to realize organization's business Analytics vision.

Every four organizational elements throughout all the adoption phases are elaborated in above paragraphs. The complete presentation of verified ADOPT-model is illustrated in the following figure.

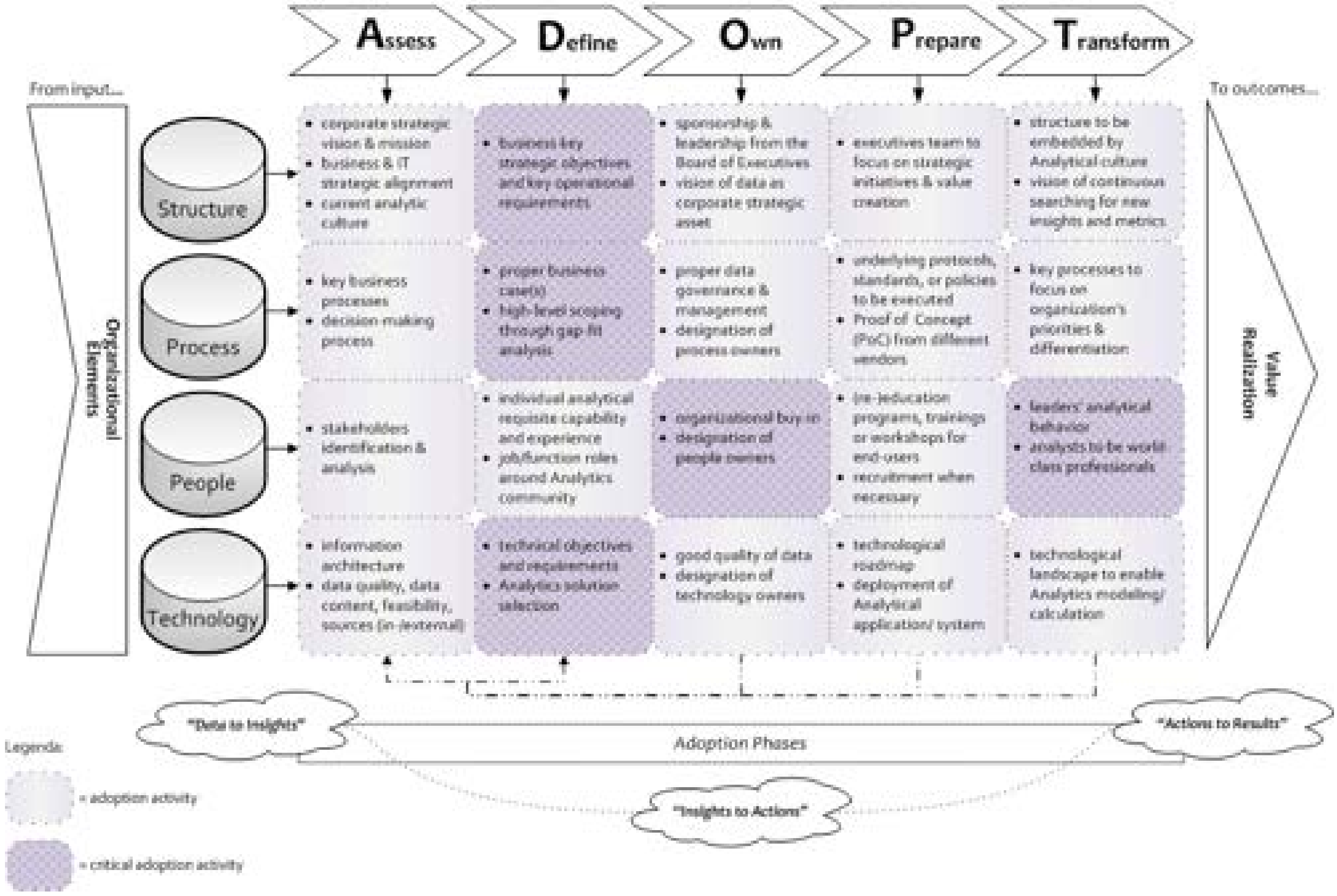

Figure 33. Complete representation of verified ADOPT-model

It is notable that the execution of the adoption process is not a sequential process, rather a continuous process that brings the organization towards the next level of Analytics maturity. The adoption process is sensitive for iterations back to the Assses-/Define-phases when subsequent phases are carried out problematically. Basically, the organization needs to reassess their initiatives and decide whether to terminate the adoption process or to return to Assess-/Define-phases to fix or tweak minor issues and go further to the next adoption phase. In addition, above four organizational elements are accounted as the eminent inputs of the Analytics adoption process, those elements are reprehensible in the capturing and storing necessary *data* into the data warehouse. These data will further be extracted, transformed, and loaded to provide *insights* to organization's decision makers. The traditional way of making decision allows managers or decision makers to act based their intuition. In contrast to that, today's staggered economic situation demarcates them to respond agilely to the market demand and to take *actions* based on facts. The ramification of a fact-based action brings *value realization* to be the output of Analytics adoption process.

6.5 Summary

The first global theme represented how the Analytics current situation is. Different areas within an organization have adopted Analytics mainly to support the Finance, Supply Chain, Human Resources and Marketing functions. Most desired analytical capabilities by organizations were balance scorecards, dashboarding, static/ ad-hoc reporting, predictive monitoring, process and pricing optimization. The major Analytics vendors identified were SAP, SAS, IBM, Oracle, and Microsoft. Organizations tend to use selection criteria before they choose their Analytics vendor, these criteria encompasses what their underlying available system is, their adoption costs, the enabling functionality, integration possibilities, and some other minor criteria. Diverse organizational traits were attempted to be recognized for those that have adopted Analytics or those that were interested in adopting Analytics. The main traits cover the fact that those organizations were innovative organizations, have a high competitive market, must comply with government's regulations, have big data, and must own Analytics in order to operate their primary business.

Secondly, the diversified cases of the adoption process have been evaluated. Most perceived adoption challenges in term of Structure were the cultural issue, organizational buy-in, the fact that there was no mandate from the upper level, and how to manage people's expectation. In term of Process, the challenges perceived by the respondents were concerning the accountability of the process owners and setting up a solid business case. As mentioned by most of the respondents, organizational people were the most challenging factor in adopting Analytics. This included to get the right people on board, to have organizational buy-in in the operational level, and how to deal with the embedded former way of working. The last organizational element, Technology, has been mostly considered to be merely an enabling factor to adopt Analytics instead of the most important element from other three elements. However, organizations tend to perceive the challenges in realizing a good quality of data and data ownership. In addition, the most critical adoption phases recognized by the most respondents were during the Define-phase in terms of Structure, Process and Technology. In term of People, the respondents have experienced equally critical during the Own- and Transform-phases.

The verification of the ADOPT-model can be referred to the result of representation in Figure 33. The feedback and evaluation of all respondents have refined and generated the initial ADOPT-model. Each organizational element has been flagged with the most critical phase(s) in order to create the awareness for the organizations to carefully handle those matters when they have decided to move forward with Analytics. Further, these analysis results and the quality of the results are reflected in the next chapter.

Chapter 7
REFLECTION

"Life can only be understood backwards; but it must be lived forwards."
~ Søren Kierkegaard

7.1 Introduction

The research study conducted by the researcher has generated a new Analytics adoption model to be applied in organizations. Nevertheless the research approach of this study still has several limitations, which will be further explained in Chapter 8.3, mainly the small-scale availability of experts as well as organizations that have adopted Analytics. This area is reflected in Chapter 7.2 and followed by a discussion concerning the reliability and validity of the research in Chapter 7.3. A brief reflection from the researcher towards the research process is conveyed in Chapter 7.4.

7.2 Reflection on Research Results

Due to the relatively small set of samples involved, the research results that have been presented in this thesis are not generalizable for the adoption process in all types of organizations (Boyce & Neale, 2006). However, the presented ADOPT-model is still able to depict substantial insights in adoption process that can deepen and widen the understanding of Analytics adoption from respondents' experience accumulated thus far. Prior to the construction of the ADOPT-model, the researcher provided a thorough analysis of the Analytics market situation surrounding the Analytics adoption in organization. Luna-Reyes and Andersen (2004) indicated that qualitative data and their analysis play a central role at all levels in the modeling process. In this manner, the in-depth analysis of current market situation consolidated the building process of ADOPT-model. Although the validation of the ADOPT-model was not intended in this research project at the first place, still it is desired when ADOPT-model is really recognized by both practitioners and scientists to potentially solve practical adoption issues or create added value to the academic knowledge base. Nonetheless, the researcher has managed to verify the ADOPT-model during the interview sessions with the field experts. The structure verification is firstly tested based on the personal knowledge of the model builder which also can be found in relevant literature, and then extended in including criticisms by others with direct experience from the real system (Forrester & Senge, 1980).

Next to the construction of ADOPT-model itself, other research analysis results are compelling to be reflected to the relevant literature. The engagement of upper level management as early as possible has appeared to be crucial in the development of Analytics initiatives in an organization. Lederer and Mendelow (1989) have postulated that IT executives need the supports from the top management to mandate a planning process for business-IT coordination. A standalone IT management efforts are not sufficient to achieve this coordination (Lederer & Mendelow, 1989). As the applications of Analytics function merely as decision support tools for the decision makers, organizations need leaders with Analytics vision and inspiration to sustain long-term success (Cokins, 2012). The

Information Management agenda of organizations that undertake the journey into business Analytics applications must treat data and information as their strategic assets (Lustig et al., 2010).

In many cases of company failures, executives who are just human and can make mistakes, caused enormous miscalculations that can be explained as the problems in leadership (Cokins, 2012). Executives are required to have personal qualities of mitigating the risks instead of creating risks. They contribute considerably in making few big decisions while employees make hundreds to thousands of small decisions every day. Albeit, the most difficult and time-consuming contribution of any major organizational transition would be changing the basic business processes and behaviors of the organization and its people (Davenport & Harris, 2007). This creates the greatest constraint on rapid motion through the adoption phases portrayed in the ADOPT-model.

7.3 Quality of the Results

The reflection on the quality of the results is explained in this section. Some researchers have claimed that the definition of reliability and validity in qualitative research is different than in quantitative research (Golafshani, 2003; Luna-Reyes & Andersen, 2004; Verhoeven, 2008). Morse et al. (2002) have stated that the reliability and validity in qualitative inquiry was rejected in the 1980s and simultaneously has resulted a shift in “ensuring rigor” of a research. Golafshani (2003) has stipulated that the reliability and validity are treated separately in quantitative studies in contrast to the terminology such as *credibility*, *transferability*, and *trustworthiness* which encompass both. The credibility in qualitative research depends on the ability and effort of the researcher (Golafshani, 2003). Furthermore, Thyer (2001) has suggested that the accuracy of data recording and the empirical and logical interpretations of data could be ensured by employing research methods. In this manner, the reliability and validity of the qualitative studies can be enhanced. Nonetheless, the following paragraphs attempt to reflect the reliability and validity of this research study separately.

7.3.1 Reliability

As mentioned above, some researchers have considered the definition of the reliability and validity of qualitative research to be questionable and carry a lot of criticisms. Verhoeven (2008) has appointed the first criticism of reliability in qualitative research to be involved in the precondition that the study should be replicable. It means to produce similar results under similar conditions. According to her, there is no clearly defined setting since qualitative research employs an open approach where models are developed during the course of the project. Therefore the replicability of the research is diminished and correspondingly the reliability is difficult to check (Verhoeven, 2008). The question needs to be raised here is whether the effort of the researcher to find answers to the questions of this research is reliable. In accordance with researchers mentioned above, a clear answer would be difficult to convey. However the researcher has attempted to increase the degree of reliability of this study by using research methods (Thyer, 2001; Verhoeven, 2008), by taking careful steps as described in the following bullets :

- a solid research framework was constructed prior to the research execution as well as the central questions of the research, which subsequently used as the reference or starting points of the research.

- all interviews sessions with respondents were audio-recorded and conducted based on homogeneous interview protocols where the justification of the central questions was covered in a semi-structured interview method.
- interview transcripts were sent back to the respondents for justification of text data prior to data analysis. The transcripts were then processed systematically using QDA software, NVivo.
- the researcher had a single and direct contact to all respondents and went personally throughout research design, data collection, data analysis, and results interpretation.

7.3.2 Validity

The second point of criticism that has been conveyed by Verhoeven (2008) regarding the quality of the research result is the generalizability and the content validity. As this research has involved a small group of experts and not a random sample, the generalization of the research results could be questionable. Likewise whether the construct should be measured or the instrument that is used to measure is the most important issue, whether the researcher is really measuring what is supposed to be measure. In this case, the perception of interview respondents stands centrally. However, the validity of this research can be seen as to minimize any biases within the qualitative analysis, such as:

- all information gained from the respondents were audio-recorded, which also increases the reliability of the results. Notes made during the interviews sessions were kept in a log.
- all text data were analyzed by using an underlying analysis method, namely Applied Thematic Analysis. On the top of that, the data was systematically analyzed by theme coding technique and accordingly presented by generating thematic networks.
- before interview sessions were carried out, a set of respondent selection criteria was set up and all selected respondents were accounted as experts in the field of research study. Additionally, the 'snowball' method took a big role in obtaining a number of respondents.

After taking above bullet points carefully into account, the reliability and the validity of this research study can be increased (Verhoeven, 2008). Concerning researcher's ability and skill in qualitative research, the reliability is a consequence of the validity in a research study (Patton, 2002). In this manner, there is no validity without reliability (Lincoln & Guba, 1985).

7.4 Reflection on Research Process

The early stage during the conceptualization of the study area was the most remarkable affair in this research. Searching for the right research direction and shaping a solid research design were considered as a cumbersome process. As being a novel researcher, exploring an obscure domain seemed to be a never-ending story or sometimes lost in a complete unacquainted circuit. Due to the fact that the chosen study domain (i.e. the adoption of Enterprise Analytics) was a relatively 'new' study, the journal articles supporting this topic were not many and widely available. Instead, more of available white papers, applied science books, or company's files were studied. However, the research progressed greatly during the data collection and analysis. Although there were limited eligible experts based on the respondent's selection criteria, a 'snowball' method seemed to work very well to get to the next respondent. The respondents were mainly approached through reference from one's social network. Overall, this research project was carried out according to the initial project planning and has been a great journey getting in contact with a qualitative research study.

Chapter 8
CONCLUSIONS AND RECOMMENDATIONS

"I am a writer of books in retrospect. I talk in order to understand; I teach in order to learn"
~ Robert Frost

8.1 Introduction

This last, but not least, chapter will recapitulate the insights gained after the research project is utterly accomplished. Each of the research questions are answered in the section discussing the main research findings in Chapter 8.2. Main critical success factors are conveyed in Chapter 8.3 for the practitioners as their guidance when Analytics initiatives have emerged in their organizations. Subsequently the limitations identified in this research project is reflected in Chapter 8.4 and followed by the direction of possible future research in Chapter 8.5 as the closure of this thesis.

8.2 Research Findings

After several interviews have been conducted and data was processed, potential answers to the research questions formulated earlier in the beginning of this research project can be profoundly grounded from the analysis results explained thoroughly in previous Chapter 6. In this section, all research questions are called back and accordingly the answers. The main research findings are obtained as the ramification of *the exploration of common Analytics adoption process in facilitating organizations in their transformation towards analytical competitor*, which is the objective of the research project. Before the solution to the main research question can be given, five sub-questions will be attempted to be answered first. The first sub-question was:

RQ1. How do organization characteristics differ in the extent of adoption of Enterprise Analytics? What are the key differentiators attached to organizations that have adopted or interested in adopting Analytics in their organizations?

No straightforward specific organization characteristics were drawn out from the information shared by the respondents. However the organization characteristics differ insignificantly with regard to the industry type of an organization, rather specific functional units were identified whereas the most Analytics applications are often adopted. This is concerning the *financial unit* of an organization, where often particular reporting is required by the government regulation (regulation compliances), the enterprise resource planning where efficient governance of organization resources can be carried out including the *supply chain* for logistics, and *human resources* department including scheduling of employees, etc. Sometimes for *marketing* purposes when customer profiling or segmentation needs to be done to customize the organization's product/services offering to their targeted customer segments. Nevertheless, peripheral characteristics attached to organizations that have adopted or are interested in adopting Analytics were discussed in particularly in section 6.2.5.

RQ2. Which key factors are essential in facilitating or inhibiting Analytics adoption in medium-to-large enterprises?

There are some ways in answering this research sub-question. However, the key factors accounted to have influence in the adoption of Analytics are the four organizational elements chosen as the focus of this research. Hence, the organizational *structure, process, people*, and *technology* are the key factors that can significantly facilitating or inhibiting the Analytics adoption in the organization. Depends on how the organizational structure is of an organization that can encourage its employees to pamper Analytics culture in the organization or how Analytics is applied within the structure of organization, silo-based or enterprise-wide, etc. How the complex business processes are clearly defined and understood by the end-users or project executors, can impact the Analytics adoption rate. How organizational people react to the cultural shifts, to be accounted for an ownership of new process/ people/ data, or how the organizational buy-in is achieved in the organization, determine the willingness or reluctance to adopt new things in the organization. In term of technology, depends on which technology solution is opted and how well this solution is deployed and implemented, whether this technology can enable the organization to achieve business values from Analytics. Nevertheless a general remark was made that the most critical factor is considered to be the people organization as the enabler to execute the entire adoption process, and then followed by how the organization structure is and how various processes are defined in the organization. The least critical but still have a substantial role is how the Analytics solutions is deployed in the technology itself.

RQ3. Which adoption phases are accounted to be the most critical phase to endure?

The answer to this question was identified as a specific theme during the data analysis that can be referred to section 6.3.5. for further elaboration. However, it was notable that most of the time the respondents pertain to *define-, own-, and transform*-phases to be the critical phases throughout the adoption process. Overall remarks as to define the future state is a decisive phase to progress further to the next phase, while to own the precondition situation might not always be cumbersome to endure. Anyhow the real transformation of the organizational elements could acquire a lot of attention as well as tension in the organization to be able to achieve the target goals.

RQ4. Does this conceptual model adequately provide consistent approaches and describe clear adoption process in order to achieve new business value offered by Analytics?

During the primary data collection, the initial design of ADOPT-model was evaluated by the field experts. After few interviews were conducted, the information gained from previous interview was accumulated and used to feed back the themes to the subsequent interviews. Continuously building the intimacy requires the complementary reciprocity from the information exchanges during the interview, in which the process of verification in the research process begins (Gubrium & Holstein, 2001). The proposed conceptual ADOPT-model is clearly described to the extent of providing a high-level overview and guidelines in fostering the Analytics adoption that is evolving within organizations in the Dutch market. However, a lower-level or detailed description of every intersection between the organizational elements and the adoption phases could be set up when desired.

Finally, the answers to the sub-questions have led the remedy to solve the research main question. Recalling the main question from section 1.2.3, this was stated as follows:

"How to transform an organization towards an analytical competitor?"

The development of the ADOPT-model as shown in Figure 33, provides a clear and systematic visualization of the crucial business activities that need to be undertaken to transform the organizational analytical capabilities. As the ADOPT-model has been verified by Analytics experts, organizations may want to consider those steps need to be taken before they really want to be an analytical competitor. The ADOPT-model can be employed by organizations or consultants to train or give workshops for their clients in order to deepen and widen the understanding around Analytics adoption as to accelerate the transition period. Nevertheless, it is notable to understand that the development of a system model is an iterative process. Each iteration results in a better and more robust model (Luna-Reyes & Andersen, 2004). Further, the next chapter provides the recommendations for the practitioners on the critical success factors in adopting Analytics that are summarized and presented in Table 8.

8.3 Recommendations for Practitioners

As mentioned earlier in the practical relevance of the research, this study can contribute to the understanding of Analytics adoption process as the proposed ADOPT-model has been empirically tested in the context of wide adoption across organization. This section endeavors to pass on some success factors identified in this research project as the recommendations for the practitioners. The critical success factors are summarized and systemized as follows:

STRUCTURE	1. Organizations must *own the buy-in* from the Board of Executives level, the CxOs and the top managers. This sponsorship needs to be obtained in a priori. 2. *Top-down approach*. The top level management should support or facilitate the integration and cultural shifts across of the organization to be promptly accepted. 3. Organizations must see *data as their strategic asset* and foster the *fact-based culture* in their decision-making processes.
PROCESS	1. Organizations need to be able to *clearly define the flows of their various processes*, so improvement on the processes can be brought correctly. 2. Identify the *relevant added business value* by putting the business needs and the potential benefits can be gained from Analytics adoption next to each other, including its related costs, in a well-formulated business case and possible to conduct gap-fit analysis before. 3. Organizations need a proper *data governance and data management* to be in place. The process-, people-, and data ownership must be assigned to responsible people who are willing to be accountable for their ownership(s). 4. Target processes should *be in coherent with the former processes* and close to organizational culture, not to change drastically.
PEOPLE	1. *All relevant stakeholders must be identified and analyze* correctly as well as getting the right people on board. 2. Define *proper new job roles or functions* and plan wisely for additional education programs, trainings, or workshops are necessary to pamper employees' Analytical capabilities. Carry out external recruitment when necessary. 3. *Be aware of the cultural shift*. People might be reluctant to change their conventional way of working before Analytics is adopted into the new prescribed way. 4. *Organizational buy-in*. Supports from all level of organizations are essential during the transition period until the project goes live, especially the synergy from the end-users. This will bridge the cultural shift a lot easier as well.
TECHNOLOGY	1. Organizations must have a *clear vision of their technology development* and how their *technology landscape should be*. 2. *Good quality of data* is the golden rule. 3. *Select the best fit Analytics applications/ tools* based on both business- and technical requirements to support their organization. 4. ***"Think big, start small"***, as mentioned by one of the respondents. First start with a very limited scope for the complete stack of technology to be implemented in focusing the structure vertically. Later expand it in horizontally, which means inserting more data, more business rules, or higher quality.

Table 6. Critical success factors in adopting Analytics

8.4 Research Limitation

The major limitations of the research projects were recognized to be associated with the chosen qualitative data collection method and the nature of the research study itself, which was exploratory. Despite the fact that the interviews provide more in-depth information than for instance, surveys, the responses from interview participants were *prone to biases*. The responses from the consultants and clients could be biased due to their stake in promoting Analytics to be adopted, amount years of experience, gained expertise, or for a number of other reasons. Moreover, the research project was conducted and the interpretation of research findings was interpreted by a novel researcher who was supposed to be appropriately trained in interviewing techniques and to minimize any potential biases that might occur. Therefore this research was prone to have a modest credibility as conducting a qualitative research depends on the ability and the effort of the researcher (Golafshani, 2003), which can be referred to the discussion with regards to the reliability and validity of the research in section 7.3.

Other limitation that has been aware of prior to the research execution was the *time bounded* in conducting the research project for six to seven months, included the internship at Accenture. This led to a single possibility in collecting, processing, and analyzing of *a small data sample* of respondents and *a limited range* of industry sectors. As the interviews can be time-intensive (Boyce & Neale, 2006), a sufficient sample size was not doable to be reached within the given time of execution. The samples were taken based on the willingness of consultants to participate in this study, and from clients representing a few industry branches in the Netherlands and not fairly distributed across different industry sectors. Therefore no random samplings were used. This resulted that the research findings are *not always valid to be generalized* for all type of organizations. Furthermore, as one of the findings was related to the government regulations in the Netherlands, this matter is subject to further investigations as different regulations might apply to other countries or regions.

In addition, the availability of academic literatures concerning the adoption of Analytics in organization was very much limited as well as the experienced consultants in adopting predictive Analytics, in particular. The immaturity of the adoption of Analytics in the Netherlands as discussed in section 1.2, has contained vicious circle whereas this study at one hand needs sufficient data (primary source e.g. experienced Analytics adopters) to draw up a contribution to the knowledge base and at other hand sufficient scientific literatures are essential to underpin the execution of this research study. Nevertheless, these limitations allow the opportunities for further research studies which will be conveyed in the next section.

8.5 Direction for Future Research

In responding the limitations of this research study as mentioned above, further research could emphasize more in the validation of the conceptual model. This thesis has presented the ADOPT-model for the adoption of enterprise Analytics as the key finding of this research, which was verified in section 6.4. Further investigation into this conceptual adoption model is suggested to clarify and confirm the findings of this research. The participation of a greater number of experienced consultants and a much wider range of client organizations from different industry sectors would provide severe research results and aid the generalisability of the findings. Another interviews round among other consultants validating the verified conceptual ADOPT-model could build a theoretical model as to extent to a Grounded Theory approach. Alternatively, employing a quantitative research method or pluralism methodology could triangulate the research findings that not merely strengthen the validity of the research result but also deepening and widening one's understanding concerning the phenomenon at stake (Olsen, 2004). In these manners, the research results can be employed as a starting point to the establishment of a rigor Analytics adoption model in organizations.

Since an exploratory study has been advocated to find the relationship among factors that influence and interact within the phenomenon, a more detailed explanation or understanding on how to adopt Analytics in organization can be set up emphasizing each of organizational elements. This could be as to construct the strategy roadmaps in transforming the organizational people or technology. A step-by-step instruction would provide the practitioners more in-depth understanding and guidance to transform their organizations to be more analytical. Furthermore, when the Analytics market becomes more developed in the Netherlands, a set of 'best practices' stories could be presented to instruct or inspire other organizations to appropriately adopting Analytics. However, further research studies should be aimed to accelerate the development of Analytics market in order to facilitate organizations to achieve their business values.

REFERENCES

Accenture. (2010). Operating Model Strategy: Services Overview Retrieved 27 July, 2012, from http://www.accenture.com/us-en/Pages/service-operating-model-strategy-summary.aspx

Accenture. (2012). Analytics Overview April 2012.

Arthur, W. B. (1991). Designing Economic Agents that Act like Human Agents: A Behavioral Approach to Bounded Rationality. *American Economic Association, Vol. 81, No. 2*(Papers and Proceedings of the Hundred and Third Annual Meeting of the American Economic Association), 353-359.

Attride-Stirling, J. (2001). Thematic Networks: an Analytic Tool for Qualitative Research. *Qualitative Research, Vol. 1 (3),* 385-405.

Berson, A., Smith, S., & Thearling, K. (2002). *Building Data Mining Applications for CRM*. Delhi: Tata McGraw-Hill.

Bhushan, N., & Rai, K. (2004). *Strategic Decision Making*. London: Springer.

Blenkhorn, D. L., & Fleisher, C. S. (2001). *Managing Frontiers in Competitive Intelligence*. Westport, USA: British Library Cataloguing.

Bloomberg, & SAS. (2012). The Current State of Business Analytics *Where Do We Go From Here?* : Bloomberg Businessweek Research Services.

Bose, R. (2009). Advanced analytics: Opportunities and Challenges. *Industrial Management & Data Systems, Vol.109 No.2*, pp.155-172.

Boyce, C., & Neale, P. (2006). Conducting In- Depth interviews: A Guide for Designing and Conducting In-Depth Interviews for Evaluation Input: Pathfinder International.

Burstein, F., Holsapple, C., Negash, S., & Gray, P. (2008). Business Intelligence

Handbook on Decision Support Systems 2 (pp. 175-193): Springer Berlin Heidelberg.

Chan, Y. E., & Reich, B. H. (2007). IT Alignment: what have we learned? *Journal of Information Technology, Vol. 22*, 297-315.

CNNMoney. (2011). Fortune Global 500 Retrieved 1 June 2012, from http://money.cnn.com/magazines/fortune/global500/2011/countries/Australia.html

Cokins, G. (2012). Why do large, once-succesful companies fail? *Analytics*.

Corbin, J., & Strauss, A. (2008). *Basics of Qualitative Research (3rd ed.)* (3e ed.). Thousand Oaks, CA: Sage Publications.

CurachConsulting. (2008). Business Operating Model Design Retrieved 27 July 2012, from http://www.curach.com/_fileupload/Curach%20Operating%20Model%20ver1_0.pdf

D'Aveni, R. (1997). Waking up to the New Era of Hypercompetition. *The Washington Quarterly,* pp. 183- 195.

Davenport, T. H., & Harris, J. G. (2007). *Competing on Analytics*. Boston, Massachusetts: Harvard Business School Publishing Corporation.

Davenport, T. H., Harris, J. G., & Morison, R. (2010). *Analytics at work: smarter decisions, better results*: Harvard Business Press.

Deloitte. (2012). Business Operating Model (BOM) Design Retrieved 27 July, 2012, from http://www.deloitte.com/view/en_CH/ch/insights/privatebankingcentreofexcellence/securingmediumtermsustainablegrowth/businessoperatingmodeldesign/index.htm

Devlin, B. (2010). Beyond Business Intelligence. *Business Intelligence Journal, Vol.15, No. 2*.

Dijksterhuis, M. S., Bosch, F. A. J. v. d., & Volberda, H. W. (1999). Where Do New Organizational Forms Come from? Management Logics as a Source of Coevolution. *Organization Science, Vol. 10, No. 5, September-October 1999*, pp.569-582.

Eckerson, W. (2011a). A Practical Guide to Advanced Analytics

Eckerson, W. (2011b). What is in a Word? The Evolution of BI Semantics Retrieved 3 April 2012, from http://www.b-eye-network.com/blogs/eckerson/archives/2011/02/whats_in_a_word.php#

Economist. (2012). Absent Friends Retrieved 1 June, 2012, from http://www.economist.com/blogs/graphicdetail/2012/01/daily-chart-10

Elam, J. J., Huber, G. P., & Hurt, M. E. (1986). An Examination of the DSS Literature (1975-1985), in E.R. McLean & H.G. Sol (eds). *Decision Support Systems: A Decade in Perspective*, pp. 239-251.

Emory, C. W., & Cooper, D. R. (1991). *Business Research Methods*. Boston, MA: Irwin.

ESDS. (2011). Exploring Diverse Interview Types Retrieved 1 August, 2012, from http://www.esds.ac.uk/qualidata/support/interviews/intro.asp

Evans, P., & Wurster, T. S. (2000). *Blown to Bits: How the Economics of Information Transforms Strategy*. Boston: Harvard Business School Press.

Forrester, J. W., & Senge, P. (1980). Tests for Building Confidence in System Dynamics Models. *TIMS Studies in the Management Sciences, Volume 14*, 209-228.

Gangadharan, G. R., & Swami, S. N. (2004). *Business Intelligence Systems: Design and Implementation Strategy.* Paper presented at the 26th International Conference, Cavtat, Croatie.

Gartner. (2011). Gartner Forecasts Global Business Intelligence Market to Grow 9.7 Percent in 2011 Retrieved 18 February 2011, from http://www.gartner.com/it/page.jsp?id=1553215

Gartner. (2012). Gartner Says Fewer Than 30 Percent of BI Initiatives Will Align Analytics Metrics Completely with Enterprise Business Drivers by 2014 Retrieved 28 February 2012, 2012, from http://www.gartner.com/it/page.jsp?id=1891515

Genesereth, M. R., & Nilsson, N. (1987). *Logical Foundations of Artificial Intelligence*. San Mateo, CA: Morgan Kaufmann Publishers.

Glaser, B. G., & Strauss, A. L. (1967). *The Discovery of Grounded Theory: Strategies for Qualitative Research*. Chicago: Aldine.

Golafshani, N. (2003). Understanding Reliability and Validity in Qualitative Research. *The Qualitative Report, Volume 8*(Number 4), 597-607.

Gubrium, J., & Holstein, J. (2001). *Handbook of Interview Research*. London: Sage.

Guest, G., MacQueen, K. M., & Namey, E. E. (2012). *Applied Thematic Analysis*. Thousand Oaks, CA: SAGE Publications, Inc.

Henderson, J. C., & Venkatraman, N. (1993). Strategic Alignment: Leveraging information technology for transforming organizations. *IBM System Journal, Vol. 38, NOS 2 &3*, pg. 472-483.

Herschel, G. (2007). The Role of Analytics in Adding Value to Business Processes: Gartner.

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design Science in Information Systems Research. *MIS Quarterly, Vol. 28 No. 1,* 75-105.

Holsapple, C. W., & Sena, M. P. (2003). The Decision-Support Characteristics of ERP Systems. *International Journal of Human-Computer Interaction,, Vol. 16, No.1*, pp. 101-123.

Howitt, D., & Cramer, D. (2008). *Introduction to Research Methods in Psychology* (2nd ed. ed.): Prentice Hall.

Johnson, G., Melin, L., & Whittington, R. (2003). Micro Strategy and Strategizing: Towards an Activity-Based View. *Journal of Management Studies, Vol. 40*(1), 3-22.

Kaplan, R. S., & Norton, D. P. (2001). *The Strategy-Focused Organization: How Balanced Scorecard Companies Thrive in the New Business Environment*: Harvard Business School

Kiron, D., Shockley, R., Kruschwitz, N., Finch, G., & Haydock, M. (2011). Analytics: The Widening Divide *Research Report Fall 2011*: MIT Sloan Management Review and IBM Institute for Business Value.

Kumar, S. (2010). Analytics: Why Gut Feel is Just Not Enough (Vol. September 2010): B-eye-Network.

Langlinais, T., Peterson, M., & Peters, D. (2008). Strategy in Action - Transforming Your Operating Model for High Performance in the Digital World: Accenture.

Laursen, G. H. N., & Thorlund, J. (2010). *Business Analytics for Managers*. Hoboken, New Jersey: John Wiley & Sons, Inc.

LaValle, S., Hopkins, M. S., Lesser, E., Shockley, R., & Kruschwitz, N. (2010). Analytics: the New Path to Value *Research Report Fall 2010*: MIT Sloan Management Review and IBM Institute for Business Value.

LaValle, S., Hopkins, M. S., Lesser, E., Shockley, R., & Kruschwitz, N. (2011). Big Data, Analytics and Path From Insights to Value. *MIT Sloan Management Review Winter 2011, Vol. 52 No.2*.

Lederer, A. L., & Mendelow, A. L. (1989). Coordination of Information Systems Plans with Business Plans. *Journal of management Information Systems, Vol. 6*(2), 5-19.

Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic Inquiry*. Beverly Hills, CA: Sage Publications.

Long, C. (2011). The Challenges of Analytics Adoption Retrieved 23 February 2012, from http://mlcwideangle.exbdblogs.com/2011/11/08/the-challenges-of-analytics-adaption/

Luna-Reyes, L. F., & Andersen, D. L. (2004). Collecting and Analyzing Qualitative Data for System Dynamics: Methods and Models. *System Dynamics Review, Volume 19*(Issue 4/ Winter 2003), 271-296.

Lustig, I., Dietrich, B., Johnson, C., & Dziekan, C. (2010). The Analytics Journey. *AnalyticsMagazine.com*.

Lynch, R. L., Diezemann, J. G., & Dowling, J. F. (2003). *The Capable Company: Building the Capabilities That Make Strategy Work*: Blackwell Publishing Ltd.

Malterud, K. (2001). Qualitative Research: Standards, Challenges, and Guidelines. *The Lancet, Vol. 358,* 438-488.

McLellan, E., Macqueen, K. M., & Neidig, J. L. (2003). Beyond the Qualitative Interview: Data Preparation and Transciption. *Field Methods Vol. 15*(1), pg. 63-84.

Montero, I., & León, O. G. (2007). A Guide for Naming Research Studies in Psychology. *International Journal of Clinical and Health Psychology, Vol. 7*(3), pg. 847-862.

Morris, H. D. (2010). Business Analytics and the Path to Better Decisions (Vol. September 2010): IDC.

Olsen, W. (2004). *Triangulation in Social Research: Qualitative and Quantitative Methods Can Really Be Mixed*. Causeway Press. Retrieved from http://research.apc.org/images/5/54/Triangulation.pdf

Op 't land, M., Proper, E., Waage, M., Cloo, J., & Steghuis, C. (2009). Enterprise Architecture: Creating Value by Informed Governance (pp. pg. 5-48): Springer.

Patton, M. Q. (2002). *Qualitative Evaluation and Research Methods*. Thousand Oaks, CA: Sage Publications, Inc.

Pearlson, K. E., & Saunders, C. S. (2004). *Managing and Using Information Systems: a Strategic Approach*. New York: John Wiley.

Porter, M. E. (2006). What is Strategy. *Harvard Business Review, Volume 74, Number 6*.

Power, D. J. (2007). A Brief History of Decision Support Systems Retrieved from DSSResources.COM, http://DSSResources.COM/history/dsshistory.html, version 4.0, 26 April, 2012

Power, D. J., & Sharda, R. (2009). Decision Support Systems *Handbook of Automation* (pp. 1539-1548): Springer.

PwC. (2011). Operating Model Design. In PwC (Ed.).

PwC. (2012). Turning Strategy into Reality Retrieved 20 July, 2012, from http://www.pwc.co.uk/consulting/issues/transforming-your-operating-model.jhtml

Riessman, C. K. (2008). *Narrative Methods for the Human Sciences*. CA, USA: SAGE Publications.

Rosing, v., & Rosenberg. (2011). Applying Real-World BPM in an SAP Environment (Vol. SAP Press 2011).

Ross, J., Weill, P., & Robertson, D. (2006). *Architecture as Strategy: Creating a Foundation for Business Execution*: Harvard Business School Press.

Russom, P. (2010). Unified Data Management *A Collaboration of Data Disciplines and Business Strategies* (TDWI Best Practices Second Quarter 2010 ed.): TDWI (The Data Warehousing institute).

Sahay, B. S., & Ranjan, J. (2008). Real Time Business Intelligence in Supply Chain Analytics. *Information Management & Computer Security, Vol. 16 No. 1*, 28-48.

Sekaran, U., & Bougie, R. (2009). *Research Methods for Business* (5th ed. ed.). West Sussex, UK: John Wiley and Sons, Ltd, Publication.

Simon, H. A. (1979). Rational Decision Making in Business Organizations. *The American Economic Review, Vol. 69, No. 4*(Sep., 1979), 493-513.

Taylor, J. (2011). Putting Predictive Analytics to Work in Operations: Decision Management Solutions.
Tesch, R. (1989). *Computer Software and Qualitative Analysis: a Reassessment*. New Brunswick, NJ: Transaction Books.
Thyer, B. A. (2001). *The Handbook of Social Work Research Methods*: SAGE.
Verhoeven, N. (2008). *Doing Research: The Hows and Whys of Applied Research* (2nd ed. ed.). Amsterdam: Boom Academic.
Verschuren, P., & Doorewaard, H. (2010). *Designing a Research Project* (2nd ed.): Eleven International Publishing.
Yin, R. K. (2009). *Case Study Research*. Thousand Oaks, CA: Sage.

APPENDIX A. Research Project Timeline

This section depicts an overview of the research project timeline starting from the first day as a new hire at the client company until the presentation and defense of this Master Thesis. The research activities and the execution periods are summarized and structured in the table below.

No.	Month	Activities	Milestones◊ and Deliverables*
1.	February 2012	- Start of internship at Accenture (New Hire Days) - Preliminary literature study - Problem analysis at Accenture	
2.	March 2012	- Plan for the kick-off meeting with the Graduation Committee - Desk research - In-depth literature study - Development of initial conceptual operating model	- Final Research Proposal* - Kick-off meeting◊
3.	April 2012	- Development of interview protocols - Respondents scanning/ selection - Approached respondents - Preliminary data collection	
4.	May 2012	- Data collection and processing - Preliminary data analysis	
5.	June 2012	- Data collection and processing - Data analysis - Set up a draft research report	
6.	July 2012	- Data processing - Verify the proposed conceptual ADOPT-model - Work on draft research report	
7.	August 2012	- Data analysis - Complete Master Thesis report draft - Plan for the 'green light'- meeting - End of internship at Accenture	- Completed draft of Master Thesis* - 'Green light'-meeting◊
8.	September 2012	- Submit final Master Thesis report - Preparation of Master Thesis presentation and defense	- Final Master Thesis report* - Presentation and defense of Master Thesis◊

Table 8. Research project timeline started from February to September 2012

The preparation of the research project has been started earlier than on February 2012 as to search for a research topic, apply for an internship, and follow the hiring procedure at *Accenture*. The internship has been officially started on the 1st of February 2012, albeit was effectively started on the second week of February due to New Hire Days on the first two days at the company. The preliminary of research problem analysis was carried out by getting in contact with Accenture's (senior) managers in order to get a clear view of issues at hand. The kick-off meeting for Master thesis project took place at the beginning of March. Setting up the complete draft version of Master thesis report was intended to be carried out as earliest as possible once research materials were available which was actually started at the end of June. The entire month of August was intended to finalize the Master thesis report, which the internship contract was terminated in the end of the month. The complete draft of Master thesis report was aimed to be delivered at the end of month as well, and subsequently planned for the green light. At the end of September 2012, a Master graduation presentation and defense was scheduled.

APPENDIX B. Typology of Various Operating Models

B.1. Accenture's Operating Model

A consultancy company *Accenture* describes an operating model as the way of a business building its capabilities to execute its business strategies (Langlinais et al., 2008). An operating model presents what capabilities are needed by the organization, and how each capability is further designed in terms of four organizational elements, i.e. people, process, structure, and technology, to improve efficiency and effectiveness. The constructed capabilities are needed in forming an end-to-end strategic value chain. A business strategy underlies the construction of an operating model and typically defines a clear target of business segments in which the operating model strategy will serve. The capabilities should be identified that can differentiate the organization in the market and should be compelling for customers to choose the product/ services provided by the organization. Additionally, the operating model must be able to define where to locate these capabilities, whether to span across functions or for specific business silos (Accenture, 2010).

B.2. Deloitte's Business Operating Model

Deloitte, a business advisory firm, applies a similar perspective of how an operating model facilitates an organization with a strategic transformation. A Business Operating Model (BOM) provides a translation of organization's strategic objectives into a coordinated set of implementation activities. The BOM depicts how and where the organization's components, relating to a process, people, and technology perspective, are to be constructed and to take action in accordance with the predefined strategy. An optimal communication and coordinated alignment in the adoption of organizational change can also be assured with the formation of a business operating model (Deloitte, 2012).

B.3. Curach Consulting's Operating Model

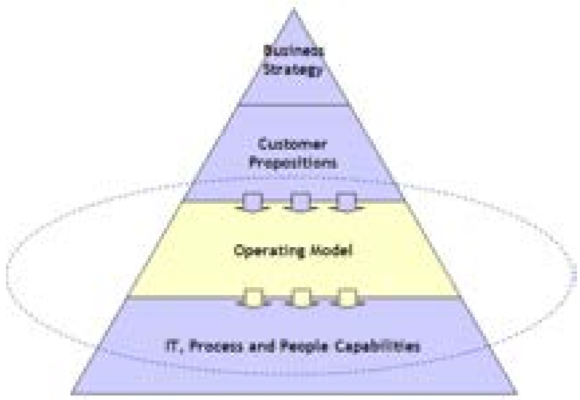

Figure 34. Operating model environment

A former leading Irish owned consultancy firm, *Curach consulting,* constructs an operating model by configuring people, organization, processes, and technology together to deliver customer propositions of the product or service (CurachConsulting, 2008). The operating model framework represents a blueprint of how tasks supposed to execute, where those tasks should take place and by whom. Fundamental capabilities are enhanced to support customer propositions by decreasing cost, maximizing revenue, and improving customer alignment. According to their perspective, an operating model can be located in a scope within an enterprise as illustrated in Figure 34. People, organization, process, systems, and measurement are considered to be important to describe holistically for the fundamental improvement, as well as the nature of customer demand. Due to the probability of radical change in economic environment, these demands are likely to change significantly and therefore crucial to be timely anticipated. A typical designed operating model represents the as-is model and to-be model for both business core and non-core activities that can be seen on the figure below.

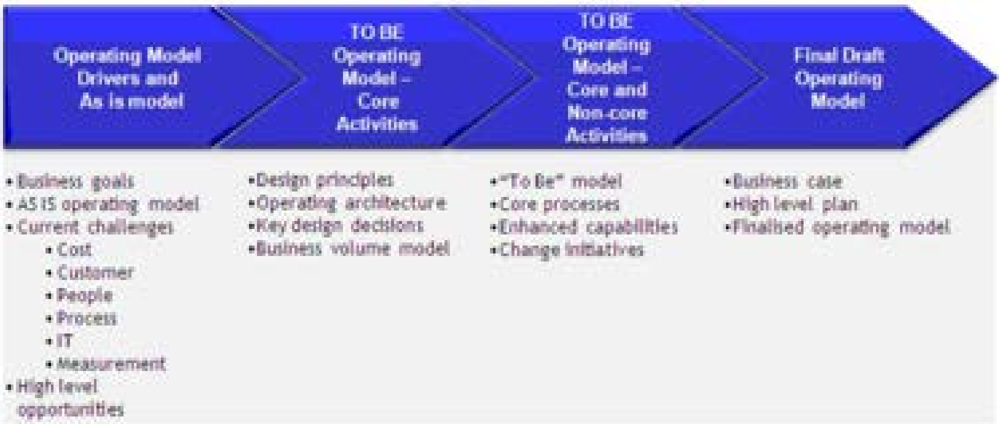

Figure 35. Curach Consulting's Business Operating Model Review

B.4. PricewaterhouseCoopers' Operating Model

An advisory company, PricewaterhouseCoopers (PWC) acknowledges the need of an operating model to respond to strategic challenges evoked by the global recession (PwC, 2012). They believe that an operating model is the way in which a business is managed to execute firm's operational decisions in order to deliver the strategy. The model should be structured in a way that the business to be responsive to change and allow quick changes in capturing opportunities. It is essential for an organization to obtain the right information for the right people in a right time. They have designed an operating model framework to help their clients in assessing the current operating structures and in establishing strategy-driven and customer-oriented organizations. The framework is used to empower their clients in tackling the challenges that have direct influences on the operational architect and their business processes (PwC, 2011).

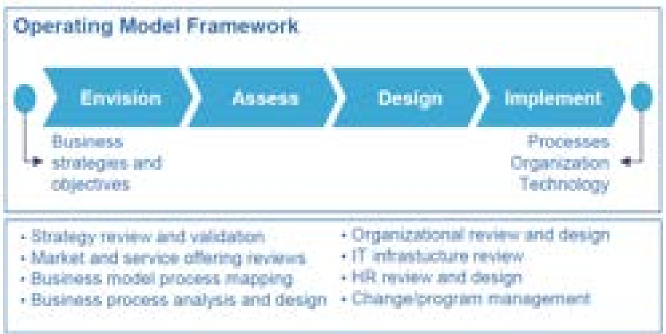

Figure 36. PwC's Operating Model Framework

APPENDIX C. Analytics Related Framework

A renowned model is treated here as a supporting model to the proposed ADOPT-model; Davenport and Harris' *Five Stages of Analytical Competition.* There are several other similar well-known maturity models from various domains such as *Gartner's maturity model for Web Analytics*, the *Capability Maturity Model Integration (CMMI)* from the Software Engineering Institute at Carnegie-Mellon University, and the *Business Intelligence Maturity Model* from TDWI. Those models present five to six progressive stages of an organization's maturity level in different areas beyond technology capabilities but also the management, business process, or the bureaucratic within organizations. However the main purpose of these models conformed to pinpoint where the organization's (analytical) initiative is at the moment and where it should go next. Accordingly, these models should be able to address certain dimension at which a successful (analytical) organization stands and guide an organization moving towards higher level/ stage.

Davenport's Analytics Maturity Model

The presentation of Davenport's analytics maturity model exemplifies the way of assessing organization's current analytical readiness. This maturity model, as other homologous capability models, describe the path an organization can pursue started from having no analytical capabilities to a champion analytical competitor but rather more focusing in the analytical capabilities owned in enterprise-wide. This is the reason why this model is considered as a good aid to support in the *assess*-phase of ADOPT model. Indirectly, the ramification of this model underpins the foundation of *define*-phase in determining organization's target maturity level and further desired state in the future. The five stages maturity model proposed by Davenport is depicted in figure below.

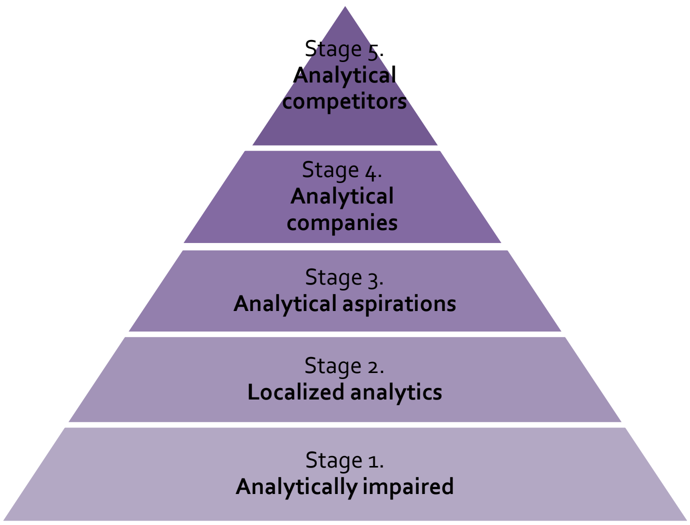

Figure 37. Davenport's analytics maturity model

Assessing the degree of analytical competition starts from evaluating the data situation within organization and the managerial interest in Analytics. Organizations at *stage 1* typically have some desire to become more analytical, but they are lacking interests in analytical competition on the part of senior executives, and the enabling skills on both human and technical resources. These organizations are denoted as *analytically impaired* and still focusing on building the basic, integrated transaction functionality and high-skills to carry out comprehensive analysis. If by any chance, they have any analytical activities then the scope is very small and local.

Organizations that are positioned at *stage 2* typically having a *localized analytics* approach and compared with having “business intelligence” in place, but they do not escalate to the standard of competing on Analytics. The organization runs disconnected analytical processes with a very narrow focus and owns pockets of isolated analysts for instance merely in finance, marketing or supply chain functional units. In terms of technology, recent transaction data is un-integrated, sometimes missing important information and isolated BI or Analytics efforts.

As the organizations value more of the benefits and promise of analytical competition but they are still facing capabilities impediments and far away from disentangle them, these organizations are recognized as the *analytical aspirations* at *stage 3.* These organizations potentially start to be analytical competitors although a long road map still needs to accomplish. Awareness and commitments from the executive board of the organization are alive with coordinated objectives of building analytically based on insights through enterprise-wide planning. BI tools are extensively used in multiple business areas, analysts are found around the organization but still with limited interaction, and the most important that the executive supports for fact-based culture to be cultivated within organization.

At *stage 4*, reaching almost the highest stage of analytical maturity, *analytical companies* merely needs to improve a few minor hurdles to be fully dedicated to compete on analytics. These organizations have already the requisite analytical skills but lack the passion to target to and compete on their distinctive capability. With only a small tweak in every organizational element, these organizations are ready to take off. The C-level is not only being supportive of an analytical focus but should be passionate about competing on analytics as well.

Last but definitely not least, at *stage 5*, where all *analytical competitors* support clearly on their organization’s distinctive capability by embracing approach in enterprise wise. Broad management commitments and passions drive organization’s analytical initiatives aiming in sustainable business benefits. Their business processes are very much fully embedded and much more highly integrated within organization, highly skilled in-house analysts that are centralized and mobilized, and immense BI/BA architecture is implemented across enterprise.

As Davenport and Harris have propounded that the five different characteristics are rather to be denoted as *stages* rather than *levels,* since for most organizations it is better to pass those progressively. Organizations that are in a hurry to reach the highest analytical stage are doomed to carry a higher risk in experiencing any major negative impacts from the organizational change. The greatest challenging would be changing the foundation of business processes and organizational behaviors including its people (Davenport & Harris, 2007).

APPENDIX D. Interview Invitation Letter

TU Delft
Delft University of Technology

accenture
High performance. Delivered.

Amsterdam, 31 May 2012

Dear Sir/ Madam,

My name is Meriane Natadarma and I am currently conducting a research project together with Delft University of Technology and a consulting company Accenture. The general idea of the research study is to get more insights on the adoption of Analytics in organizations. The research study endeavors to cover the following questions:

> *which characteristics are attached to organizations that have adopted Analytics or to organizations that are interested in adopting Analytics; what kind of Analytics applications do organizations need or desire to adopt to achieve a new business value offered by Analytics; which essential factors can facilitate or inhibit Analytics adoption, and what are other potential factors that might affect Analytics adoption.*

The results will be useful in the deployment of Analytics applications within organizations in order to capture the business value offered by Analytics solutions.

I would like to invite you to be a part of my research study. Your knowledge and experience in this matter will assist me in providing recommendation to improve the dispersion of Analytics adoption, especially within the Dutch market. Your cooperation in an interview session is very much appreciated and will lead to a greater understanding on how this matter takes place in practice. The interview session will not last more than one hour. All information given by you or your organization will be treated in strict confidence and will only be used for the purpose of this study. Upon request, the outcomes of this research can be shared to you as well.

It would be greatly appreciated if you would participate in the interview session, preferably before **29 June 2012**. Please contact me by e-mail or phone to plan our interview session. Any further questions regarding the research project can be referred to me or to my supervisor within Accenture, Olaf Penne, at olaf.penne@accenture.com.

I thank you for your time and cooperation.

Yours faithfully,

Meriane Natadarma
M.Sc. Candidate in Management of Technology
E-mail: meriane.natadarma@accenture.com
meriane8@gmail.com
Mobile: +31 6 422 422 06

Faculty of Technology, Policy and Management
Delft University of Technology
Delft, The Netherlands

Accenture – Process & Information Management
ITO Toren, Gustav Mahlerplein 90, 1082 MA Amsterdam
P.O. Box 75797, 1070 AT Amsterdam
The Netherlands

APPENDIX E. Interview Protocol for Consultants

TU Delft
Delft University of Technology

accenture
High performance. Delivered.

Background Information

Name of participant	:	....
Email address	:	....
Mobile phone *(optional)*	:	....
Job position/ level	:	....
Area of responsibility	:	....
Work experience *	:	.... year(s)

** regarding DW/ MDM/ BI/ Analytics work field*

Recording Confidentiality

For the sake of source reliability and being an aid during data analysis, this interview session will be fully recorded. The content of this interview will be processed anonymously and the outcome of this interview will be shared to you. Upon request, the end result of this research study can be shared to you as well, which can be used as guidance for future reference regarding Analytics adoption.

Participant signature,

.... , ... / ... / ......
[Place] [Date]

INTERVIEW PROTOCOL

RESEARCH STUDY OF ANALYTICS ADOPTION WITHIN ORGANIZATION

Date: ____ / ____ / 2012

Time: ______ - ______

INTRODUCTION

Good morning/ afternoon,

First of all, I would like to thank you for your participation in this research study. My name is Meriane Natadarma and I am doing a research project together with Delft University of Technology and a consulting company Accenture. The general idea of this interview is to get more insights from the adoption of Analytics in organizations. The focus of the research is on how to transform an organization to be Analytical competitor. This interview will endeavor to cover the following questions:

> *which characteristics are attached to organizations that have adopted Analytics or interested in adopting Analytics; what kind of Analytics applications do organization need or desire to adopt in order to achieve a new business value offered by Analytics; which essential factors can facilitate or inhibit Analytics adoption, and what are other potential factors that might affect Analytics adoption.*

Next, I will briefly describe how we will manage this interview. The interview will last approximately for one hour. There will be three question rounds which comprise the questions regarding a current situation of Analytics market and trends in general, followed by core questions regarding the model evaluation emphasizing in four organizational elements, and few of concluding questions at the end.

ROUND 1 – ANALYTICS MARKET & TRENDS

1.1 Which organizations have you been/ are doing Analytics projects with?

1.2 In which area of implementations have client organizations adopted Analytics?

1.3 Which Analytical capabilities have client organizations achieved/ desired to achieve?

1.4 Which Analytics vendors are mostly opted to be adopted in client organizations?

1.5 How do you distinguish the selling points of different Analytics vendors and offer to clients?

1.6 How usually client organizations select their Analytics vendor?

ROUND 2 – MODEL EVALUATION

(See attachment "ADOPT – Enterprise Analytics Operating Model")

2.1 In which operating phase (A, D, O, P, or T) do client organizations have mostly difficulties to progress in term of organizational *structure*?

2.1.1 How do you elapse this phase? Any specific actions required to exercise?

2.2 In which operating phase (A, D, O, P, or T) do client organizations have mostly difficulties to progress in term of organizational *process*?

2.2.1 How do you elapse this phase? Any specific actions required to exercise?

2.3 In which operating phase (A, D, O, P, or T) do client organizations have mostly difficulties to progress in term of organizational *people*?

2.3.1 How do you elapse this phase? Any specific actions required to exercise?

2.4 In which operating phase (A, D, O, P, or T) do client organizations have mostly difficulties to progress in term of organizational *technology*?

2.4.1 How do you elapse this phase? Any specific actions required to exercise?

2.5 What tools are available and applicable for each operating phase?

2.6 Based on your experience and knowledge, is there adjustment applicable to this ADOPT operating model?

ROUND 3 – CONCLUDING QUESTIONS

PATTERN RECOGNITION

3.1 What characteristics are attached to client organizations that have adopted Analytics or interested in adopting Analytics?

3.2 What kind of Analytics applications do client organizations need or desire to adopt in order to achieve a new business value offered by Analytics?

BARRIER & RISK

3.3 What concerns do you mostly perceive/ anticipate during the adoption of EA in client organizations?

SUCCESS CRITERIA

3.4 In your opinion, what are the success criteria in adopting Analytics in client organizations, in terms of *Structure, Process, People,* and *Technology*?

3.4.1 Which essential factors facilitate Analytics adoption in client organizations?

3.4.2 Which essential factors inhibit Analytics adoption in client organizations?

CLOSING

3.5 Are there any questions you would like to ask regarding the research project?

3.6 Is there anything else you would like to share with me?

THANK YOU!

I would like to thank you for your time and co-operation during this interview. I really appreciate your willingness to participate in my research. All information gathered through this interview will be processed and translated into a non-literal transcript. The transcript comprises the summary and themes emerged during the data processing, and it will be sent back to you for possible correction or adjustment. For further remarks or questions, please do not hesitate to contact me. This is the end of the interview session. Once again, thank you!

----- ***Have a Nice Day*** ☺ -----

APPENDIX F. Interview Protocol for Clients

TU Delft
Delft University of Technology

accenture
High performance. Delivered.

BACKGROUND INFORMATION

(Tick box when applicable)

Name of participant : ....
Email address : ....
Mobile phone (optional) : ....
Job position/ level : ....
Area of responsibility : ....
Name of the organization : ....
Industry sector : ....
Number of employees :

- ❑ between 250 and 499
- ❑ between 500 and 999
- ❑ more than 1000

Annual revenues (in Euros) :

- ❑ less than 225.000
- ❑ between 225.000 and 500.000
- ❑ between 500.000 and 2.500.000
- ❑ between 2.500.000 and 5.000.000
- ❑ between 5.000.000 and 20.000.000
- ❑ more than 20.000.000

Recording Confidentiality

For the sake of source reliability and being an aid during data analysis, this interview session will be fully recorded. The content of this interview will be processed anonymously and the outcome of this interview will be shared to you. Upon request, the end result of this research study can be shared to you as well, which can be used as guidance for future reference regarding Analytics adoption.

Participant signature,

.... , .../ ... / ......
[Place] [Date]

INTERVIEW PROTOCOL

RESEARCH STUDY OF ANALYTICS ADOPTION WITHIN ORGANIZATION

Date: ____ / ____ / 2012

Time: ______ - ______

INTRODUCTION

Good morning/ afternoon Sir/ Madam,

First of all, I would like to thank you for your participation in this research study. My name is Meriane Natadarma and I am doing a research project together with Delft University of Technology and a consulting company Accenture. The general idea of this interview is to get more insights from the adoption of Analytics in organizations. The main focus of the research is on how to transform an organization to be Analytical competitor. This interview will endeavor to cover the following questions:

> *Which characteristics are attached to organizations that have adopted Analytics or interested in adopting Analytics; what kind of Analytics applications do organization need or desire to adopt in order to achieve a new business value offered by Analytics; which essential factors can facilitate or inhibit Analytics adoption, and what are other potential factors that might affect Analytics adoption.*

Next, I will briefly describe how we will manage this interview. The interview will last approximately for one hour. There will be three rounds of questions that comprise the questions regarding the current situation of overall performance of your organization, followed by core questions regarding four organizational elements, and some supplement questions at the end.

ROUND 1 – CURRENT SITUATION QUESTIONS

1.1 Has your organization adopted any of Analytics applications? [Yes/No]

[If yes]

1.2 Which Analytics applications is your organization currently using?

1.3 Which provider is your organization using?

1.4 How do you select your Analytics provider? Is there any criteria selection? If yes, please describe them.

[If no]

1.5 Why has your organization not yet adopted Analytics?

1.6 Have you ever considered adopting Analytics? Can you please elaborate on that?

Round 2 – Model Evaluation Questions

ORGANIZATIONAL ELEMENT 1 – STRUCTURE

2.1 How clearly defined are your organization's mission, vision/goals, and strategies/targets across the organization?

2.2 How do you describe the link between the business strategy with IT strategy/ deployment of Analytics in your organization?

2.3 Does your organization define the competitive parameters to be focused on in your market? Can you please elaborate more on what these parameters are?

2.4 How does the specification of requirements (e.g. business requirements, Key Performance Indicator (KPI), critical success criteria, performance measurement/metrics, etc.) be defined and regulated in your company?

ORGANIZATIONAL ELEMENT 2 – PROCESS

2.5 How is data used to drive decision-making processes?

2.6 How does the costs & benefits estimation, in financial term, of Analytics adoption influence the business processes and Analytics product selection?

2.7 How does your organization structure the navigational paths to access Analytics applications?

ORGANIZATIONAL ELEMENT 3 – PEOPLE

2.8 How would you describe the individual Analytical talents available in your organization?

2.9 How active is business leadership in supporting Analytic efforts?

2.10 How does your organization support the recruitment, development, and retention of Analytical talent?

ORGANIZATIONAL ELEMENT 4 – TECHNOLOGY

2.11 How does your organization govern the technical objectives and requirements?

2.12 How do you describe your organization's data, in terms of consistency, functionality, and significance?

2.13 What is the most important technical issue in adopting Analytics in your organization?

2.14 Which Analytics capabilities has your organization gained/ do you wish to gain from EA adoption in terms of organizational *Structure, Process, People, and Technology?*

ROUND 3 – SUPPLEMENT QUESTIONS

BARRIER & RISK

3.1 What concerns do you perceive/ anticipate during the adoption of EA in your organization?

SUCCESS CRITERIA

3.2 In your opinion, what are the success criteria in adopting Analytics in your organizations, in terms of *Structure, Process, People,* and *Technology?*

CLOSING

3.3 Are there any questions you would like to ask regarding the research project?

3.4 Is there anything else you would like to share with me?

3.5 Would it be possible to contact you after this interview if I have further questions?

THANK YOU!

I would like to thank you for your time and co-operation during this interview. I really appreciate your willingness to participate in my research. All information gathered through this interview will be processed and translated into a non-literal transcript. The transcript comprises the summary and themes emerged during the data processing, and it will be sent back to you for possible correction or adjustment. For further remarks or questions, please do not hesitate to contact me. This is the end of the interview session. Once again, thank you!

---- *Have a Nice Day* ☺ ----

APPENDIX G. Follow-up Interview Letter

TU Delft

Delft University of Technology

accenture

High performance. Delivered.

Delft, August 17th 2012

Dear participant,

I am sending you a non-literal transcript based upon our interview session conducted few weeks ago. Please feel free to contact me for any adjustments of feedback you wish to make, before Friday, August 24th 2012, otherwise no further action is requested. The research report will be finalized after that period, and the interview transcript attached on this email will be accounted for the final analysis.

The final research report can be shared to you approximately in the month of October.

I thank you deeply for your time and cooperation.

Kindly regards,

Meriane Natadarma
M.Sc. Candidate in Management of Technology
E-mail: meriane.natadarma@accenture.com
meriane8@gmail.com
Mobile: +31 6 422 422 06

Faculty of Technology, Policy and Management
Delft University of Technology
Delft, The Netherlands

Accenture – Process & Information Management
ITO Toren, Gustav Mahlerplein 90, 1082 MA Amsterdam
P.O. Box 75797, 1070 AT Amsterdam
The Netherlands

APPENDIX H. Applied Thematic Analysis Coding

A. Codes	B. Basic Themes	C. Organizing Themes	D. Global Themes
1. Finance 2. Supply Chain 3. Human Resources 4. Marketing 5. Asset Management 6. Risk Management 7. Enterprise Performance Management	1. Analytics adoption areas		1. Analytics market situation
8. Ad-hoc reporting 9. Static reporting 10. Dashboard	2. Descriptive Analytics capabilities	1.Desired analytical capabilities	
11. Balance Scorecards 12. Pricing optimization 13. Process optimization 14. Predictive monitoring	3. Predictive Analytics capabilities		
15. SAS Analytics/ Text Miner 16. SAP BW/ BO/ HANA 17. IBM Cognos/ SPSS 18. Oracle Hyperion/ Crystall Ball 19. Microsoft Sharepoint/ Excel 20. Open Sources	4. Major analytical vendors chosen		
21. Underlying available system 22. Adoption costs 23. Enabling functionality 24. Integration possibilities 25. Viable Proof-of-Concept 26. Purchased solution suite 27. Reference-based 28. Mandate from central office	5. Vendor selection factors		
29. Innovative organizations 30. Regulation compliances 31. Organization's primary business 32. High competitive market 33. Big data 34. Clear vision and business processes 35. Good quality data 36. Treating Analytics as a standalone discipline 37. Data seen as a strategic asset 38. Large organization	6. Typical traits of organizations considering Analytics adoption		

39. Cultural issue 40. Organizational buy-in 41. Managing expectation 42. No mandate from upper level 43. Seen as a part of IT 44. Required former way of reporting 45. Defining business vision 46. Numerous business requirements	7. Adoption challenges within organizational Structure		
47. Creating a business case 48. Accountability of process owners 49. Data governance & management 50. Process monitoring	8. Adoption challenges within organizational Processes	2.Perceived adoption challenges	
51. Getting right people on board 52. Organizational buy-in from operational level 53. Embedded former way of working 54. Individual responsibility	9. Adoption challenges within organizational People		
55. Good quality of data 56. Data ownership 57. Defining technical objectives 58. Tools selection	10. Adoption challenges within organizational Technology		2. Adoption process evaluation
59. Structure – Define phase 60. Structure – Own phase 61. Process – Define phase 62. Process – Transform phase 63. People – Own phase 64. People – Transform phase 65. Technology – Define phase 66. Technology – Own phase 67. Technology – Transform phase	11. Most critical adoption phase to progress		