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Improving business intelligence data quality in sales insight area

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Liiketoimintatiedon (eng. Business intelligence, BI) hallinta on organisaation kyky kerätä ja analysoida keräämäänsä tietoa liiketoiminnastaan ja liiketoimintaympäristöstään, ja luoda informaation ja sen analysoinnin kautta uutta tietämystä ja näkemystä organisaation ohjaamiseksi. Yksi keskeisistä asioista liiketoiminta-analytiikan kehittämisessä ja tiedon käytössä on ymmärtää tiedon laadun merkitys ja sille asetettava tavoite, samoin kuin kuinka hyvin tiedon laatuvaatimukset täyttyvät eri käyttötapojen suhteen.

Liiketoimintatiedon käyttö raportoinnin ja analytiikan tarpeisiin edellyttää eri tapahtumapohjaisten tietojen ja perus- sekä referenssitietojen mallintamista, hallinnointia ja yhdistämistä liiketoimintaa tukeviksi mittareiksi. Kun organisaation tavoitteet on liitetty osaksi mittaristoa, mittareiden avulla voidaan seurata liiketoiminnan operatiivista onnistumista ja organisaation kilpailukykyä ja -etua.

Tiedon laatuvaatimustavoitteiden ja laatumittareiden suhde liiketoiminnan tulos- ja suorituskykymittareihin on läheinen, erityisesti niiden mittareiden osalta, jotka organisaatio näkee avainmittareiksi. Tämä vaatii mittareiden taustalla olevien käsitteiden ja niiden määritelmien yhteismitallisuutta. Kun käsitteet ja niiden merkitys ovat nimenomaisesti hyväksyttyjä, määriteltyjä ja sovittu otettavaksi yrityksen liiketoimintaympäristössä käyttöön, ensimmäinen askel yhteisen tietämyksen jakamisen tiellä on saavutettu yrityksen ontologian kautta.

Tässä kuvailevassa tapaustutkimuksessa on esitetty kohdealueen eli liiketoimintatiedon tiedon laadun parantamiseen liittyviä tekijöitä erityisesti myynnin näkökulmasta. Esityksessä on kuvattu liiketoimintatiedon olemusta, ja kuinka se voidaan nähdä tiedon, informaation ja tietämyksen jakamisen kautta osana yrityksen strategista varallisuutta. Tietojoukkojen luokittelun, määrittämisen ja tietomallinnuksen avulla voidaan hallita käytössä olevia tietovarantoja. Tiedon laadun parantamisessa keskeisellä sijalla on käsiteltävän tiedon semantiikka ja ontologia, ja panostamalla näiden asioiden huomioonottamiseen organisaatiot voivat hyvinkin yksinkertaisin keinoin parantaa tiedon laadun edellytyksiä ontologian kehittämisen keinoin.

Asiasanat
Liiketoiminta, Tiedon laatu, Semantiikka, Ontologia, Tietomallinnus

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Abstract

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Business intelligence (BI) management is an ability of a business organization to gather and analyze systematically information about its business operations and the business environment it is having business in, and turn that information and analysis of the information as knowledge and insight for the business organization. One of the key topics in the business intelligence development and usage situation is to understand what is the data quality level needed to create new knowledge and understand how well those quality targets are met.

To be able to provide business intelligence for reporting and analytics purposes, different kind of transactional data along with master and reference data needs to be modeled, managed and aggregated as business metrics. When business organization is having targets for its execution, it can use the calculated and shared information and metrics to enhance its operations and competitive advantage.

Data quality targets and metrics have a close relationship to organizational performance and result indicators, especially those which are the most important for the organization as key performance/result indicators. This requires clearly defined concepts and semantics to be in place behind performance and result indicators so the metrics can be understood semantically consistently as well. In the business environment when concepts are explicitly defined, shared and agreed inside an organization, the first ground work of having a common capability for knowledge sharing has been reached and when creating a common ontology for the company.

In this descriptive case study research, theoretical framework for business intelligence data quality topics are covered by going through the semantics of business intelligence and how it is related to data, information and knowledge sharing as well as different data categories and modeling techniques. End result of this study is, that when improving data quality for business intelligence, it is crucial to focus on information semantic and ontology and to improve overall organizational data quality and knowledge sharing culture. This can be achieved by taking actually very simple principles of ontology creation in operational use.

Key words
Business, Data Quality, Semantics, Ontology, Data modeling

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Abbreviations

3NF	Third normal form
BI	Business Intelligence
COBIT	Control Objectives for Information and Related Technologies. A Framework created by ISACA for information tech nology (IT) management and IT Governance
CRM	Customer relationship management
ER	Entity-relationship. A data modeling notation.
ERP	Enterprise resource planning
ETL	Extract, transform, load. Process of extracting, transforming and loading data especially in data warehousing environment
ICT	Information and communication technology
IDEF1X	Integration Definition for Information Modeling
IE	Information engineering
IT	Information technology
KGI	Key goal indicator
KPI	Key performance indicator
KRI	Key result indicator
MDM	Master data management
OLTP	Online transaction processing
OWL	Web Ontology Language
RDF	Resource Description Framework
SCM	Supply chain management
Six Sigma	Business management strategy, originally developed by Motorola in 1986
SPC	Statistical process control
TDWI	The Data Warehouse Institute
TOGAF	The Open Group Architecture Framework
TQM	Total quality management
UML	Unified modeling language

1 Introduction

1.1 Research background

Business intelligence (BI) is an ability of a business organization to gather and analyze systematically information about its business operations and environment, and turn that information into knowledge for the business organization decision making and operational processes. Goal is to use information and analyze it to make better decisions and achieve better results than the competitors. In analytically leading companies, this can be achieved by basing the decisions on facts. Having right set of qualified data turned into meaningful facts and dimensions around the facts is also the basis for knowledge sharing and insight creation.

Amount of business data as well as raw performance level of the IT systems enabling to crunch and manage masses of data has increased enormously in the past years. Despite of this, having a lot of data or technological computational power do not remove the fact that data quality is becoming increasingly more and more important topic. If the data gathered cannot be trusted, matched, linked or integrated with other data sets, or if the meaning of the data cannot be ensured across the enterprise, reliability and lack of trust in the data can become a major problem in the decision making process and in every-day operational execution.

1.2 Research questions and purpose of the research

Different kind of things can influence in data quality, like IT systems, human, process or cultural phenomenon in the area of data management. The focus of this thesis work and research is to analyze and define how business semantics and ontologies influence on data quality. Many times IT organizations are trying fiercely to solve data quality problems as a technological issue, but if business rules, data definitions, taxonomies and ontologies are missing, systematic approach for data quality corrections is difficult or even impossible to accomplish.

The purpose of this case study research is to describe business intelligence data quality topics and to explain those potential issues if information semantics are missing or they are conflicting to each other.

The main research question was this:

- How better data semantics and ontology can improve the data quality regarding master data related quality issues?

Following sub-questions related to main research question were researched as well:

- What is the role of conceptual data modeling to lead towards better data semantics and ontology?
- Why it is difficult to agree and to have common data definitions to be used across an organization?

1.3 Research strategy

The research strategy was based on case study research using practice-oriented descriptive approach. In practice-oriented case study work, research project phases consists of searching literature of the subject area as well as using existing information available and having discussions and interviews with the practitioners who deal with the topic in an organization to identify the problems and prioritization of the research topics (Dul & Hak 2008, 33-34). Because the researcher was already having a joint effort with specific business and IT capability development programs and projects during the research working time, practice-oriented case study approach was a natural choice for research method.

1.3.1 Motivation for the research study

Sales information of the products and services (service can be seen as a product itself) and their success is ultimately in everybody's interest in any company. Without having good profitable revenue growth companies cannot succeed or even exist. Therefore sales business data and data around the sales is foundational data for any business organization to manage and analyze. Insight creation about the sales, or insight creation

for the sales organization cannot reduce its' focus only to sales data. It is necessary to understand other influence factors affecting to sales success as well as to understand if the data available is having good enough quality to make it trustworthy for business decision making and operational usage.

1.3.2 Hypothesis and qualitative measurement variables

The hypothesis for the case study and reasoning for the knowledge creation work of this case study was that especially in large global companies having multiple data systems and data management processes, master data quality problems arise. One of the reasons for this is that people are having different meanings and semantics for the same data. When e.g. customer or product concept and their definitions are not clear, different organization units within the same organization manage and understand concepts in a different way, leading in controversial and ambiguous implementation of data management processes and IT systems.

One of the research work goals was to analyze this hypothesis in the light of real business data. The subject area of master data was chosen for this purpose and especially regarding customer and product data. Research, analysis and recommendations how well they are handled in the organization was accomplished. Lot of data quality investigations and analysis were done during the development project adjacent to this study. Since many data quality analysis had been done already during the past years, there was no lack of data quality assessment materials to study and to analyze.

Regarding the research question of "How better data semantics and ontology can improve the data quality regarding master data related quality issues", real life data quality use cases were selected for the hypothesis testing using following variables:

- Variable 1a: How customer data definition variations affect to sales insight creation when having different understanding of customer data definitions?
- Variable 1b: What are the implications of the variations to the business analytics having different kind of customer semantics and hierarchies there?
- Variable 2a: How product data definition variations affect to sales insight creation when having different understanding of product data definitions?

- Variable 2b: What are the implications of the variations to the business analytics having different kind of product semantics and hierarchies there?

1.3.3 Source of evidence

Major source for this research evidence was based on already available documentation in the subject organization, some of them being with systematically gathered data by the researcher himself during the past years. Supporting materials for the study was gathered by using document archives, and having interviews with different data management teams and email discussions to gather current state information. When examining current state and data in the data warehouse and master data environment, real life use cases and existing semantic data models was used for quantitative and qualitative analysis. Observations done by the researcher and also by various other customer and product data management persons working in the company were accomplished. Based on these data sources, a case study database was created for the study work.

This study included an exploration phase to define the problem area as precisely as possible by creating theoretical framework for the subject area and visiting and analyzing real data found in the places like data warehouses and other operational databases. Theoretical framework was created by examining existing bibliography of books, articles and other related studies available, and by making observations of data and using case specific documentation of data quality issues. These observations together with the theoretical framework defined also the needs for knowledge creation and prioritization of research topic phases in an iterative way.

After this phase, descriptive case study materials were analyzed, and the findings documented in a separate classified appendix. Based on the analysis, conclusions and propositions were made for the corrective actions. Some supporting interviews were held to cross-check the validity of the past data quality findings and to reflect what are their influence to business intelligence creation today.

1.4 Thesis project and it's linkage to related capability development work and program

The baseline for semantic comparison between existing experiments and observation of data quality was created in a separate task to support also business analytics capability development program. Renewal of conceptual master data model was also created as a sub-project, and research studies were done on the area of developing sales insight reporting and linkage between the conceptual data model and analytics capability creation activities.

One of the key things was to analyze different angles of the current state, circumstances of current organizational behavior and beliefs regarding data quality and its state, and to analyze the need for a change of improvement perspective for sales insight. Therefore as part of the development project work companywide, enterprise business information data model was created to be used also as a baseline for as-is data quality gap analyzes.

1.5 Report structure

This report is divided in two parts: publicly available part and confidential part. Case study strategy and approach is explained in details chapter 2. In the chapter 3 theoretic framework of business intelligence, data quality, data modeling principles and the linkage between them how to construct business intelligence, knowledge and insight through those frameworks are explained. Theoretical framework was used to construct the empiric part of the case study and also for proposition creation how to improve those data quality issues found during the research work from the semantics perspective. The empiric part of study is created as a separate appendix and it is company confidential information. Generalizable outcomes and findings of this empiric analysis are described in chapter 4 of this document, and overall result discussion and further suggestions for future research topics in chapter 5.

2 Research strategy

2.1 Case study approach as a research method

Typical characteristics for a case study research approach is that it is an empirical inquiry to investigate contemporary phenomenon in depth and within its real-life context, especially when the boundaries between phenomenon and the context they are happening is not clear (Yin 2009, 18).

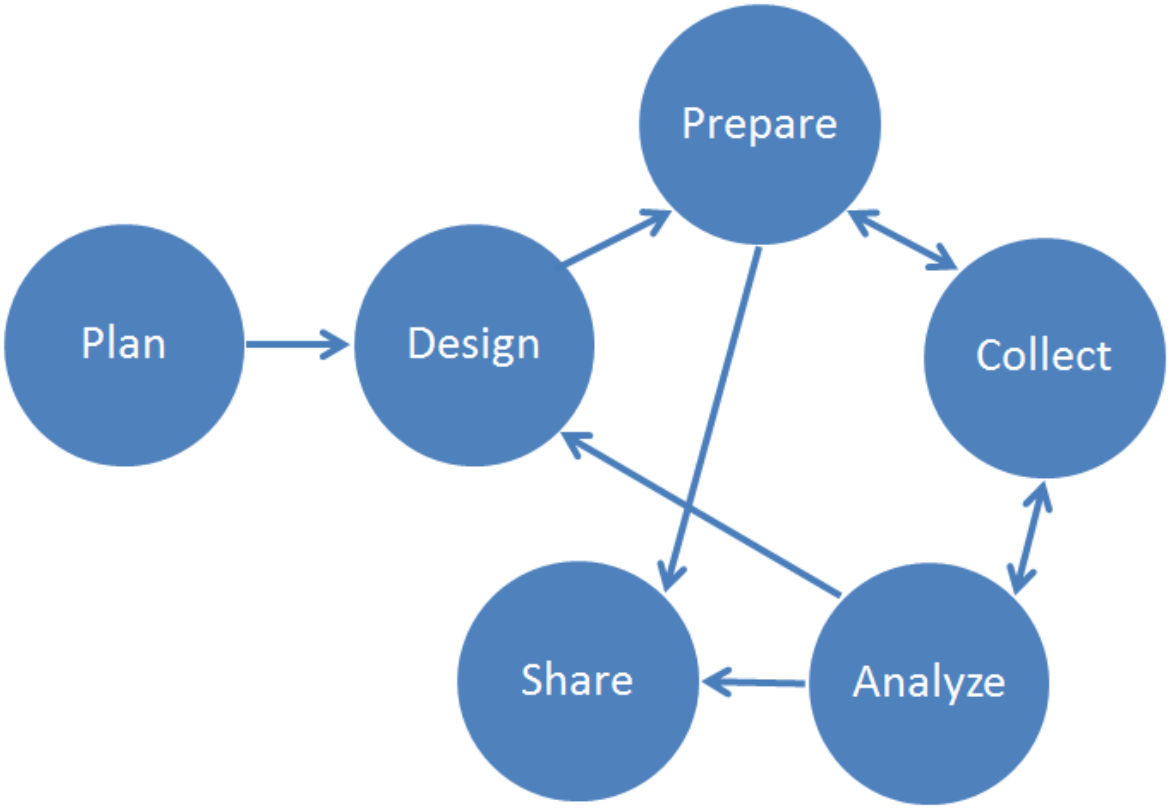


Figure 1: Case study process: linear but iterative process. (Yin 2009, 2)

Case study can be seen as an iterative research process (figure 1), which starts with a planning phase (as all research projects). In this phase research questions are identified and rationale for the research work is defined. Next phases are about to design the study, prepare for studying the subject area and outlining the problems to be covered, collecting also the evidence of the case, analyzing the data gathered about the case using possibly both quantitative and qualitative data, and finally sharing the outcome and findings with the relevant audience and composing textual and visual materials about the results of the study. (Yin R. 2009. 2, 24, 66, 98, 126 and 164).

In business research area, case study can be defined as a one single case or small number of cases (e.g. having comparative multiple case studies) that are interest of a business organization having a real life context and presenting one or more research problems to be studied, and which are analyzed and evaluated in a qualitative manner. Work organized as a research project can be theoretical or practice oriented case, where the case means an instance of an object of study. Case study is different from surveys in two ways: number of instances of from which data is collected for analysis, and the data analysis method itself. Surveys are normally quantitative (statistical) analysis of data where case study uses more qualitative aspect of case or cases, and can use earlier studies if available for more depth analysis to make conclusions. (Dul & Hak 2008, 4-6).

2.2 Theoretic-oriented case study research

In theoretical case study research the purpose of the study is to develop a theory. A theory is a set of formulated propositions about an object of study where each proposition consists of concept and specification of relations between concepts. Theory development can consist of activities of exploration, theory-building research and theory-testing research.

When theories are tested in the research work they are formulated as propositions. In exploration phase the purpose is to search if any other theories and practices exist already. This is a normal academic approach in the university and science environment. Theory or theories can be created and tested almost endlessly since the research of theory and testing the theory are the main outcomes of the research. In business environment, research has to have normally an endpoint, whether it is defined and based on by time, available resource usage or both. (Figure 2).

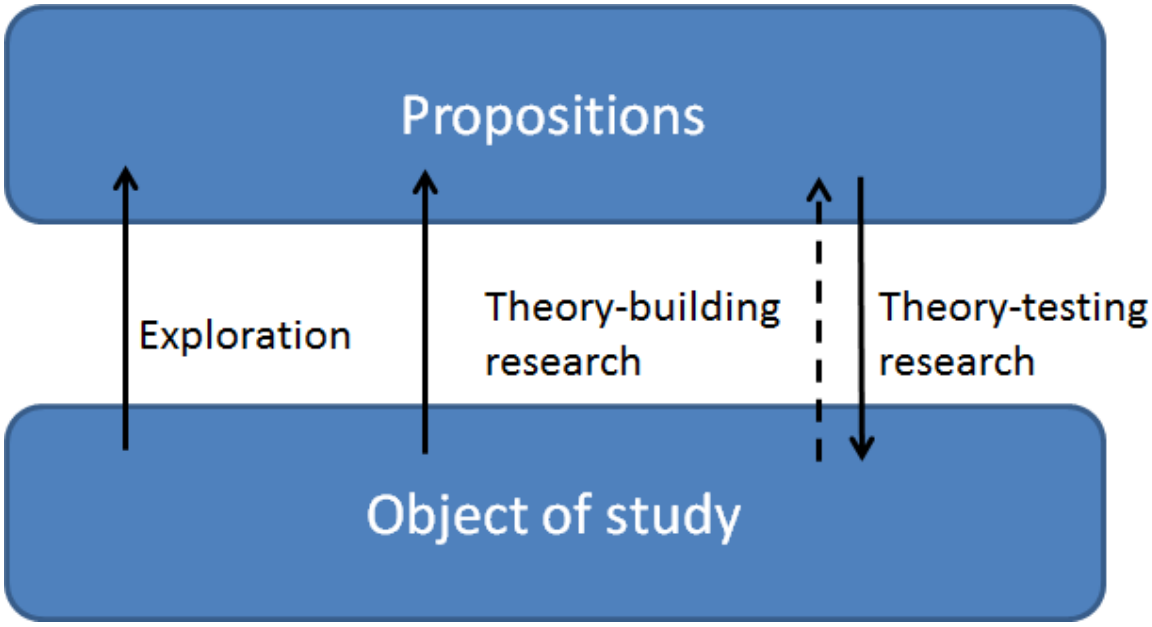


Figure 2: Theory-oriented case study research. (Dul & Hak 2008, 39).

2.3 Practice-oriented case study research

Practice-oriented case study is useful when the purpose is to deliver knowledge to the practitioners who can use the findings and create new knowledge based on the study. Practice here means responsibility, either formal or informal, to act according a real life situation. In business environment, this can mean for example an operational or business decision making situation.

The problem solving research uses an iterative intervention cycle to prioritize knowledge needs during the exploration phase. Problems are first found and identified, and their definitions are depicted as precisely as it is possible in the circumstances. Next step is to realize why a specific problem exists and what the root cause of the problem is. When this is diagnosed, next phase can be to design the intervention to solve the problem, and then implementing the solution as an intervention as it was designed. After implementation, evaluation phase can be accomplished to ensure that the goal of intervention has been achieved and if the problem has been able to be solved (figure 3). (Dul & Hak 2008, 52-59).

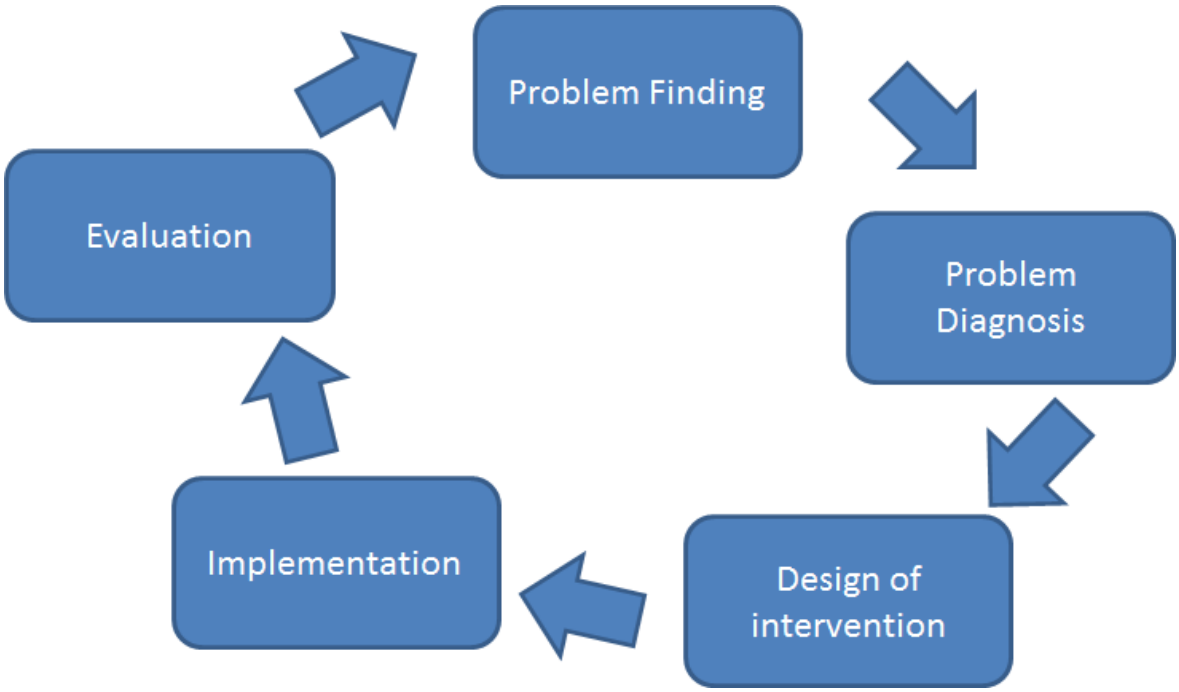


Figure 3: Practice-oriented case study intervention cycle of practice exploration. (Dul & Hak 2008, 54)

Practice-oriented case study research method can be quite similar as an action research method since the purpose of action research is to solve different kinds of real-life practical problems, to enhance social working methods and to understand them more deeply especially in a work community (Metsämuuronen 2008, 29). This work community can been naturally a business community like business organization. Normally researcher needs to be actively involved with expected benefit for a business organization and to obtain knowledge of the research subject area. Finally, the research needs to be managed as a cyclical process linking both theory and practice (Baskerville & Wood-Harper 1996, 239-240).

According to Dul and Hak (2008, 55), three are three kinds of approaches of practice-oriented case study research:

- Descriptive
- Hypothesis-building
- Hypothesis-testing

Descriptive case study research approach tries to find all relevant material about the study subject especially if a theory is missing or if researcher does not want to use any

theories to explaining the subject or to test a theory with the case. Sometimes the descriptive case study might miss concepts and terms so it might be even impossible to start with a previous research results. Therefore one major and expected outcome of the case study might be to just define definitions of concepts, and documenting them holistically as such, especially if the research is very explorative in nature. (Routio 2007).

In exploratory research a researcher wants to explain deeper the consequences and root causes of phenomenon and why things are like they are. The reasons behind explanations can have retrospective, present or prospective view of events and phenomenon. Causal roots, context specific explanations and historic analysis of things happened in the past can give new ideas for further theory creation, hypothesis-building or hypothesis testing research as well. Many times with the descriptive and exploratory case studies need extreme focus limitation so the research area does not expand too much and become too big to research and analyze. (Routio 2007).

Despite what kind of case study research approach is used, it is always good to have an exploration phase in the research subject area. If hypotheses can be found, it can be tested in a practice-oriented research project. If no hypothesis is available, then next decision is to decide whether hypothesis creation is needed or not. If no hypothesis is needed then descriptive research should be designed and executed. If hypothesis is needed, hypothesis-building approach can create the needed knowledge. If hypothesis is available and it is worth to test to create new knowledge and actions by practitioner, hypothesis-testing approach should be executed. (Dul & Hak 2008, 45-55).

If the case study is using descriptive approach but intervention and implementation of it is not part of the research work, intervention is not even possible or needed in the time frame the research is done; it might be still relevant to describe and investigate the case to find those areas and hidden constructions that have lead into the current state and find the path to the current state changes as further research ideas. (Teräväinen 2011, 8-9). Descriptive case study has its place as a research method by describing the subject of the study, documenting it and analyzing why the case has happened as it has occurred, and what kind of things are needed to be understood when considering or

comparing it to other subjects in the same area. It also takes into account the specialty of the research subject area by describing the circumstances, which, of course, can be reflected against similar cases in some extent.

In the research work, gathering information about the subject as well as gathering information about what has been already studied and is available in the literature and studies is important to discover. Six different kinds of methods for data gathering can be used. Existing documentation in many forms, like descriptive written documents, recordings or video material about the subject area is one kind of source of evidence. Documentation can be about the past, present or prediction of the future; if past, then archival records and databases are good source for information as well. Interviews with practitioners and other relevant people referring to case subject are insightful for constructing a view on causal circumstances and viewpoints. Direct observations and participant based observations as well as physical artifacts (like data warehouses or other IT tools) are one kind of sources of evidence when constructing a case study database. (Yin 2009, 101-114).

2.4 Case study success criteria

Social science research methods of validity checks can be used to evaluate success criteria of a case study. These tests are construct validity, internal validity, external validity and reliability. These validity principles can be used also in the business management as well as data management area since much of the rules of data quality management is a subject of a social and cultural behavior of an organization. (Yin 2009, 40-41).

There are also principles regarding how to collect data in a way it help and maximize to the success criteria regarding the source of evidence usage. One principle is to use multiple source of evidence. This ensures that different angles of material and input for the analysis phase are covered in a multifaceted way. Another important principle is to create a case study database. This data storage includes the data that was gathered and used for the study as well as the report produced by the researcher. It is also good to keep notes and other related documents (incl. paper or digital printouts, voice or video recording) as part of the case study database. Third principle is to maintain a chain of

evidence so that the case study questions, linkage between the questions of study protocol and link to evidence material is logical, visible and can be tracked also through case study database including the end result of the case study as a case study report. The citation in case study report should visually link the chain of evidence so that external validator can also repeat or further study the findings represented in the report. (Yin 2009, 114-124).

2.4.1 Construct validity

One of most challenging tests is to evaluate if the case study is constructed, designed and defined correctly, and if research topic and assumptions of the case are valid and not just impressions done by the researcher himself. Important tactic to create valid construct is to identify correct operational measures and use multiple sources of evidence, establish chain of evidence and to give key informants a chance to review draft case study report. Phases regarding these activities cover data collection and composition. (Yin 2009, 41-42).

Construct validity can be analyzed through four areas as content, convergent, discriminant and nomological validity. Content validity is about how logically the content is managed to measure and is the content valid for measurement or for qualitative analysis. Convergent validity is looking how scores in a testing environment correlate to other scores in other tests assessing the same construct. Discriminant validity is the degree of which scores in a test or case are not matching with other tests that are not designed to assess the same construct. Nomological validity is about how a construct is behaving similarly as similar related constructs (e.g. conformant with laws or common logic). (Changing Minds Org 2012)

2.4.2 Internal validity

For explanatory case studies, one of the biggest concerns is that causal interpretations are conducted correctly so that when creating relationship of event X leading to event Y, there are no other factors P or Z that threat the validity of conclusions. These are concerns that are needed to be done especially in data analysis phase. For descriptive

case studies, concern is not that big since they are not presenting causality reasons but a description of a situation as it appears and how it has evolved. (Yin 2009, 42-43).

2.4.3 External validity

Depending on the use cases, single case studies can sometimes be difficult to generalize. This requires relevant theory creation which needs to be tested with a solid theoretical framework. This is done in the design phase. If multiple cases are selected to be studied, those needs to be conducted separately, and conclusions across cases to be done as a separate task, also ensuring and keeping in mind that the theory might need to be updated. (Yin 2009, 43-57).

2.4.4 Reliability

When focusing on the reliability, one of the most important things are to avoid errors and biased approach to the subject area of the study. When case study includes various data gathering activities these should be documented and constructed as a study protocol, and the findings and results should be composed as a case study database. In this way, the tests can be repeated by the investigator himself and by evidence validators. (Yin 2009, 45). Thus, one of the key things is to ensure that researcher is objective towards the subject area and is not mixing subjective opinions together with the findings or conclusions.

3 Theoretical framework

3.1 Business intelligence

Business intelligence is an organizational capability where business organization is gathering information for decision support and operational purposes to make analysis and actions based on the collected information. This capability includes human resource capabilities along with information management, IT tool development and utilization perspectives.

One of the most important areas of business intelligence development is to create analytical skills and artifacts for an organization. Successful companies who develop their analytical skills focus typically work on five development areas: 1) having accessible, high quality data, 2) orientate analytical skill development towards enterprise level instead of having only randomly organized small initiatives, 3) create their leadership skills to include also analytical working culture, 4) establish strategic targets and link them analytical question and targets that make a difference to company's success and 5) organize analytical human resources and their skill development in a manner that benefits the whole enterprise and not just specific business functions (Davenport, Harris & Morison 2011, 19-22).

3.2 Leading and lagging indicators

Indicator information can be divided in two categories: leading and lagging indicator information. From business information usage perspective, lagging information is data about from the past, and this kind of information can be stored in data warehouses or operational data storage systems. This data can be utilized in performance management by analyzing past data to see if those accomplished actions and results in the past led organization to achieve its goals and targets, or not. It also provides a learning loop back capability to analyze the success of an organization strategy creation or execution success of the strategy. (Laursen & Thorlund 2010, 50-53).

Leading indicator information can be created based on information analysis by using existing lag information or by combining it with some other external information relevant for the business. Analysis can be based on different statistical analysis methods to create new lead information, like key performance indicators (KPI) to improve existing business process and ideas, or to create new ones. (Laursen & Thorlund 2010, 50-53).

Not all of the performance or result indicators are equally important. Parmenter (2010, 12-14) defines that an enterprise should not have more than ten (10) key result indicators (KRI) and key performance indicators (KPI) explaining the result. There can be tens or hundreds of team or unit specific performance indicators, but they are not the key indicators for the whole company. Many times key performance and result indica-

tors as a concept can be used quite widely and wildly in the companies today, so the meaning of something being "key" is not semantically necessarily that clear.

Parmenter (2010, 4) suggests also that the (key) performance indicator should be non-financial indicator whereas (key) result indicators are mostly financial or otherwise indicate the results of an action (Parmenter 2010, 2-7). COBIT as an IT management framework used to have term of key goal indicators (KGI) and key performance indicators, but in the version 4.1 and later on in the version 5 they are referring to two different kinds of indicators: outcome measures, and performance indicators. Outcome measures (previously KGIs) are lagging indicators, and they show if the goals have been met or not. Performance indicators show if the goals are likely going to be met, and thus performance indicators are actually leading indicators. (IT Governance Institute 2007, 22).

3.3 Data categories

3.3.1 Definition of data

Data can be seen as a representation of something. Data becomes information when the representation of something has a meaning and the content is interesting as such for somebody. Data and information are many times used as synonyms, although in reality information is data that is processed somehow for its intended use (Wang 1998, 59). In a business environment and from the business decision maker's point of view this means that data is aggregated to a level where it makes sense for a decision making process (Laursen & Thorlund 2010, 94-95). When this aggregated data has also an interpretation rule and defined semantics around the representation, data is processed as an information entity or set of entities that has business interest. When this information has clear business value for the business management, information becomes as an information asset for the company. Like any other assets, information assets need to be managed and nurtured for the business purposes.

3.3.2 Master data

Master data is all about the core objects of the business organization is working on or working with – it defines the essence of the core building blocks for business operations of a company. Along with the associated metadata it defines what matters the most for the business organization. (Loshin 2009, 5-8). Master data is non-transactional data and information about the subjects and objects of a business event. This event itself is a business transaction which involves the objects and parties of a transaction as master data items. Examples of master data is company data (e.g. parties involved in business transactions) or product data (subject of business transaction). (Loshin 2009, 15-21). Master data serves both operational transaction processing and operational usage, and also business analytics and related applications by providing dimensional data around the facts of transactions. In other words, analytical applications are using and consuming master data but do not create master data except when some derived analysis results need to be updated to master data (e.g. customer value classification in frequent flyer loyalty program when customer has reached a certain valuation level). (Loshin 2011, 337-338).

In the early days of computing history, there was no master data management (MDM) problem. The reason for this was that computing was done in a single centralized computing environment, and both the transactional and master data was handled in the same place and with the same data structures. Data was many times managed as flat files, which sometimes caused problems with data redundancy and related data maintenance problems having the same data multiplied many times in the processing time. This was largely ignored as such since applications were quite straightforwardly developed for batch environment and for a single business purpose.

Since from 80's amount of information and amount of information managing IT applications and systems have increased dramatically. This has meant that even inside one organization there are multiple systems using, updating or creating data. This applies also to master data. Workgroup computing invented in 80's with the explosion of desktop computing and relational database system development for personal usage freed the decision making capabilities from a centralized environment to decentralized or-

ganization unit level. Desktop application computing power developed in the 90's exploded the distribution of master data in several places used and managed by several organization units and teams. (Loshin 2009, 3-4).

In the mid 90's when internet services started to reach more and more business interest and importance, information management decentralization approach was not anymore the key thing but developing centralized computing environment for internet services became critical again. The same started to apply to master data management since it started to come back from the desktop and groupware applications back to more centralized place. Because of the more complicated business decision making and service offering environment, business process related application suites were created by focusing on combined business process management capabilities like customer relationship management (CRM), enterprise resource planning (ERP) and supply chain management (SCM). Unfortunately, the master data was still spread –and many times still is- typically across different business applications and application platforms serving different organizational processes. That is why master data management has become such an important topic for the business and for IT departments nowadays. In companies who have started master data management initiatives to correct the situation, master data management teams and related governance groups are trying to link and integrate master data back together with transactional data, especially when the enterprise data warehouse environment has been established. In a large scale data warehouse environment most of the business process specific data needs to be mapped and linked together so that better business decision and knowledge across processes can be shared and analyzed. This applies also to master data integration need in the data warehouse environment. (Loshin 2009, 3-4).

3.3.3 Transactional data

Transaction is data about some event. Event can be about anything that has happened, or is about to be happen (predicted event). In business environment, transactional data describes and captures those planned, predicted or actual events that take place when a business organization operates its business. Normally one transaction as an information entity (as a database record, for instance) describes one business event like sales

order intake, sending an invoice or capturing customer interaction between the business organization and a customer. (Alter 2006, 218-219). If transactional data illustrates more than one transaction, it is a presentation of aggregated transactions which means that aggregated transaction loses information about some specific individual events Laursen & Thorlund 2010, 95). Sometimes transactional data illustrates monetary operations, communication event or other interaction between parties involved in the event. These transactions can be captured as individual transactions, or being consolidated as a group of transactions together for reporting purposes.

Transactions contain data about the subject of transactions as well as data about who were the parties involved in the business event. This data is actually master data as defined in chapter 3.3.2. If handled properly, transactional data should refer or otherwise use master data handled separately from the transactional processing from the data maintenance point of view; it is not a very good practice to keep master data like customer names and addresses as part of each individual business transaction data. Instead, good practice would be to track business subjects and objects as part of master data management separately and then only referring to those master data entities in the transactional side. (Loshin 2011, 331-337).

3.3.4 Metadata – data about data

Metadata is defined in most simplistic way being data about data (Laursen & Thorlund 2010, 151). Metadata can be explaining structured or unstructured data. Metadata about unstructured data (e.g. documents having no pre-defined data model as a data structure) is mostly about textual data representation of the content and the content taxonomies. These taxonomies can be internal subject areas found inside the unstructured data representation or they can become externally driven (like Sarbanes Oxley taxonomy). Metadata referring to structured data (e.g. transactions or master data that is identifiable and organized in a structured manner in a database) can be categorized in three levels: enterprise, local and business metadata. Enterprise metadata is mostly about business semantics which defines terms of an enterprise which should also include external reference data like country codes or names. Local interpretation of enterprise metadata can vary or localized versions might have a different concept for the

global term. This is where conceptual data models both in global and local levels can help to map different words meaning the same thing, or if the same word is used to mean different things. Without understanding these metadata mappings, data might become incommensurable because of lack of semantic linkage. (Inmon, Strauss & Neushloss 2008, 95-110).

The importance of business metadata management has arisen since the early first data warehouse implementation in late 90's. It is important for the end users or business analysts to understand and know how to find data from the data warehouses or from several data marts, or if an enterprise wide data warehouse approach is in use how to find right information entities from this corporate wide data storage for new analysis purposes. This requires that you know what kind of data is stored, where and from what part of the business process data is collected. This means that some additional data is required to define the data. (Inmon et al. 2008, 95-98). The metadata to be managed for this kind of use situations can be defined in business information models as well as in logical and physical data models. Conceptual data models gives the business language, definitions and terms, which are then defined in more details in logical and lastly in physical data models showing how the business information is managed and stored in different data storages.

Metadata can be used to describe also the system of record about data subjects and their attributes. System of record defines what is the source system (and a related business process) which is providing a data entity or an attribute of it. For major data subject areas, like a customer order, there might be actually many systems providing the data for customer order attributes as a value. Business metadata can define also the rules and policies used in a business. It can also show business rules that e.g. in a sales situation, age should be captured always. The reasoning for this business policy might become from legal perspective. (Loshin 2009, 124-125).

Technical metadata can describe how the information can be represented (e.g. age is a three digit numeric field, which is always a positive integer number). Technical metadata can be used also how to transform alphabetic text field containing age information to numeric if the source systems treat data differently. This is important information

especially for extracting, transforming and loading (ETL) process used to incorporate data to data warehouse environment from various IT source systems. (Inmon et al. 2008, 223).

In master data management area, metadata management plays an important role. Business definitions and business metadata defines policies and semantics regarding master data and its usage, but it includes also reference data, data element metadata and data governance related data rules for data use, access and data quality. Reference data such as country or currency codes, although not necessarily originally created inside a company, needs to linked with other business transactional data and master metadata and to be kept up-to-date as well (Loshin 2009, 105-107).

3.4 Information modeling methodologies and approaches

Modeling is an activity to represent a thing (like some phenomenon or an object) in some other way than using the thing itself. Different kind of modeling methodologies can be used to achieve in representing things. For very high level data modeling work the notation of how to represent things is not that important because model can be pictures, drawings or other ways to describe business terms and concepts as a representation the target audience will understand easily. However, different modeling methodologies and notation methods can provide advantages to illustrate various business rules, semantics and relationships, and therefore a basic knowledge of various approaches of modeling is beneficial to know. Conceptual data models can be translated into logical and physical data models of data applications and data storages as well as dimensional data models used in the business intelligence area. (Hoberman et al. 2009, 13-28; 44)

3.4.1 Modeling techniques and notations

One of the most popular modeling methodologies is Unified Modeling Language (UML) especially when object oriented system engineering methods are used widely in a company. Entity-Relationship (ER) modeling or Information Engineering (IE) modeling methodologies are also used widely in the data storage development areas, but there are other notations used as well like Integration Definition for Information Mod-

eling (IDEF1X) and Object-Role Modeling (ORL). (Silverstone & Agnew 2009, 30-33).

IDEF1X is used many times in government institutions since its origin is in United States Department of Defense. Information engineering notation is very similar to ER-models and it is also readable with minimal training for business users since it uses boxes and lines with verb phrases in relationship lines to make it more readable. Barker notation is similar in many ways that business users would represent things in Power-point slides; e.g. subtypes of information are presented as smaller boxes inside the supertype box which would make Barker notation to look like it is not a data model at all. (Hoberman & et al. 2009, 91-101).

ORM models focus on high level concepts only so it cannot be very easily used to illustrate logical or physical data models. The power of the notation is in that it can show real life data as examples which makes it more concrete for the business users as well. Last but not least one modeling method is to describe data as natural language sentences as a document. Everybody who can read, have an opportunity to understand the rules and definitions. Since there is no notation other than alphabetic language, the danger of misinterpreting a notation as a diagram is not the case. (Hoberman & et al. 2009, 91-101). The problem might be that when considering a large business subject area, the amount of text can be substantial compared to a data model diagram which can illustrate business rules and relationships in a single page diagram and where textual presentation could take tens or even hundreds pages of written language.

Modeling notation selection is dependent of what purpose and to what kind of audience it is targeted for. Entity-relationship model notation is an ideal choice for database creation purposes and used by developers, where UML is fit for purpose for application developers focusing on object oriented development and having not only database tables creation work in mind. For business user, representing the data in an understandable format without any specific modeling notation might be good enough, for example using Excel spreadsheet format. (Silverstone & Agnew 2009, 30-33). Depending on the audience of data models, the appropriate modeling notation should be selected from the communicational aspects viewpoint. The key for making conceptual

models and data models understandable for business users is to choose a notation for the end audience so that they can understand the communication. This is also an important topic from data quality perspective to ensure that the business context, semantics, taxonomies and ontologies are understood in a similar way inside a business organization.

3.4.2 Conceptual data modeling

Conceptual data modeling a.k.a. business information modeling is about representing business terms, concepts, their definitions and semantics along with their relationships to each other. This can be done by showing concepts and terms as information entities and also showing their relationship to each other in some information usage context. In conceptual data modeling process key terms and definitions are used, described and modeled as business sees them. (Hoberman & et al. 2009, 13-43).

In the conceptual data modeling business concepts, key terms and definitions are used, described and modeled as business sees and uses them. The level of information entities are represented in a very high level without detailed attribute data (figure 4), although there can be some sample attributes just to clarify and show the characteristics of an entity (or class, if UML is used) (Hoberman & et al. 2009, 60-61). In a fact, conceptual data model is not a data model at all because it just captures business concepts and information, and how it is used in an organization (Chisholm 2012, 1-2). Conceptual data modeling is very important phase since it acts as a link to logical and physical data models. The purpose of a high level conceptual data model is to show how to control business rules and ultimately how database systems and should be managed and integrated for the business (Hoberman & et al. 2009, 57-59).

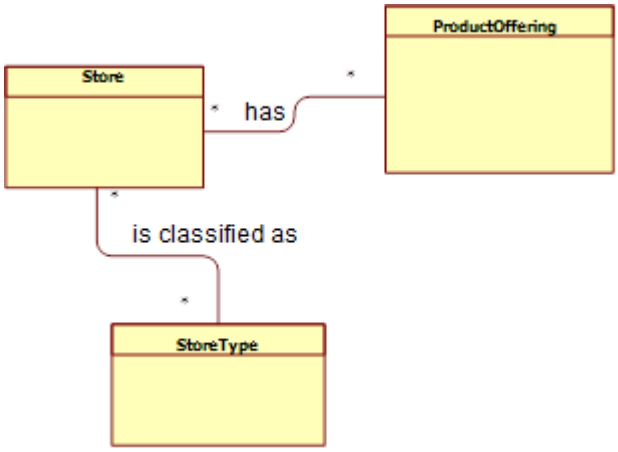


Figure 4: High level conceptual data model example

As figure 4 shows as an example, the purpose of high level conceptual model is to provide a high level view without the annoying details: that's why this is the starting point and most important part of the information modeling work. It helps business people to understand their own business operations or business processes across business units what the whole enterprise or a company is trying to achieve. Different names used for the same thing (synonym) or a same term used for a different thing (homonym) are also key to analyze from data quality management success perspective (Corr & Stagnitto 2012, 98-101). The purpose of the conceptual modeling is to find those sometimes confusing matters and at least map those discrepancies across the organization. Since the idea of conceptual data modeling is to use business language terms when constructing a view from the information perspective of business operations and their concerns, the language used in models should be the same used by the business users.

When the key concepts and terms are clear enough and information and concept definitions are agreed with the business stakeholders, the next step is to define what the business wants to do with the data and what kind of data they want to turn into information. This step also creates the first level linkage and understanding of the business processes and potential applications that might be in the scope of handling the information. This kind of work is highly iterative and needs always to be accomplished in several steps with the business stakeholders. Therefore conceptual data modeling is part of the information requirement analysis. Depending on the width of the focus area, different kind of diagrams can be used to illustrate business rules, policies, rela-

tionships and definitions of concepts. Documentation of the terms can be published as a separate glossary, so the entities in a model are clear before proceeding in to the next level of more detailed data modeling phase. Conceptual data model with visual representations are key to make a conceptual bridge between business and IT. (Hoberman & et al. 2009, 119-127).

3.4.3 Logical data modeling

When conceptual data models are in an adequate level, the next step of data modeling can occur. In the logical data modeling level the conceptual model is developed further and different kind of unclear relationships between different concepts and data entities are defined in more detail and more precisely (figure 5). This is relevant especially in the online transaction processing (OLTP) environment. In this step, data modelers define exactly the information relationships by normalizing the conceptual data models. In normalization process all many-to-many relationships are removed and modeled as one-to-many relationships by adding more data entities in the model and by analyzing the data entities in the precise data attribute level. The next more granular level of information entities might be added as well to a model to handle the business information requirements. (Corr & Stagnitto 2012, 5-6).

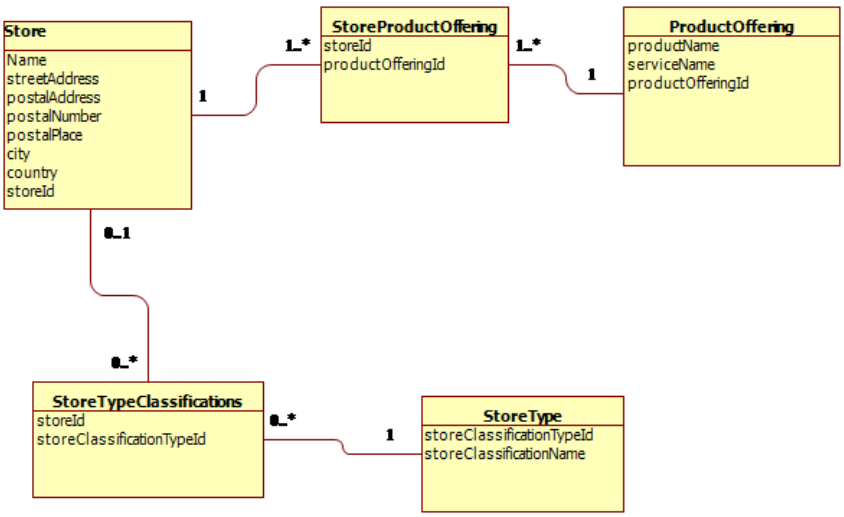


Figure 5: Logical data model example

The idea of logical data modeling is to develop the conceptual data model more close to what is going to be implemented as an information and communication technology (ICT) solution and/or database. It is still important to understand that both conceptual and logical data models are not still meant to be implemented as such and they are used for communicational purposes to enable extended group of people (like in IT side) to understand what is the information business is looking for. (Hüsemann, Lechtenbörger & Vossen 2000, 6-7).

In the ICT vendor management situations, both conceptual and logical data models are very handy in vendor collaboration, evaluation phase when vendors are providing ICT solution proposals, or when requests for proposals (RFP) are going to be sent out to vendors for vendor selection based on their answers. Using higher level data models and definitions makes external interest groups understand much better the business needs and can enable them to provide better responses for RFP's. (Takki 1999, 15).

3.4.4 Physical data modeling

The last detailed level of data modeling process is physical data model representation (figure 6). This is the thing that represents the needed specific technical implementation to fulfill business requirements depicted first as conceptual models and then in logical data models. This is also the model that connects information and the actual physical data together and how the data needs to be organized in the ICT systems so that it becomes usable for the business users. Depending on the technology used in the ICT solution, physical data models might look quite different across different tools and databases. The key thing is that the data modeler who is responsible of the logical data modeling ensures that all the information requirements defined in the logical and conceptual models are included in the final physical data model.

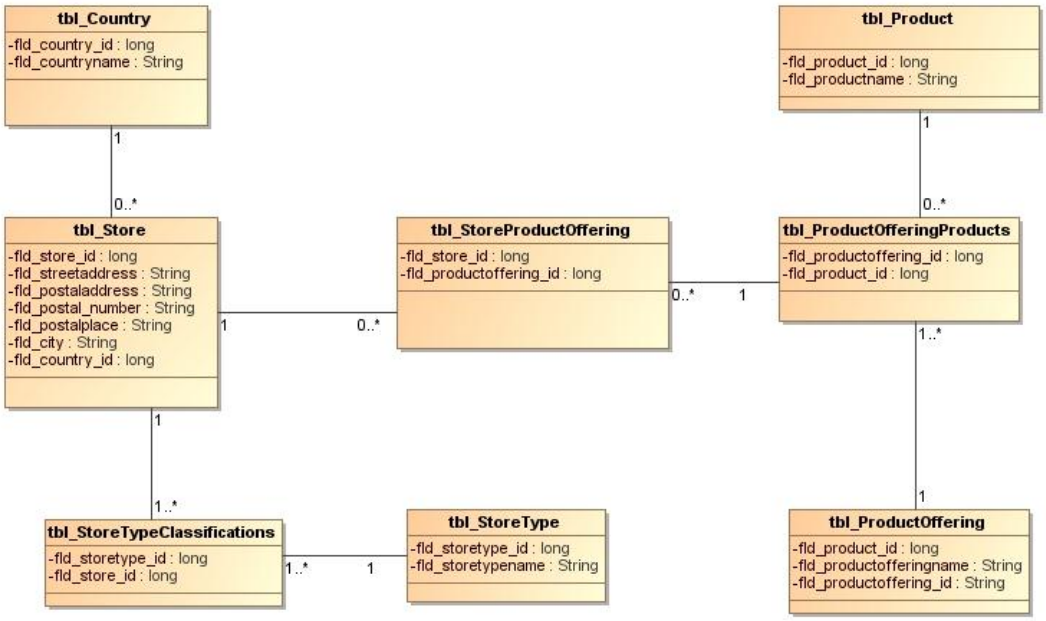


Figure 6: Physical data model example, parameterized and normalized to avoid data redundancy in OLTP environment

3.4.5 Data granularity

No matter what the level of business analytics usage company is having, pure single record level of data is too specific for decision support. For example, individual transactions of sales in certain time period might be an interesting piece of information to the operative sales person or for customers receiving a cash receipt to check he/she was invoiced correctly, but as a single piece of information this kind of individual transaction data doesn't help the company create better sales or how the company should balance the resources for the sales operations. Therefore, this kind of detailed data needs to be aggregated in the level it supports the decision making and planning operations of sales. (Laursen & Thorlund 2010, 94-95).

Information needs to be aggregated in a level it enables to analyze and create new insight of the operations, plan the business and set business targets that make sense. In the aggregation of data, data semantics and definition of the data needs to be understood. Aggregating right data but with wrong semantic hierarchy or classification definitions creates analytical ambiguity since the analysis outcomes are not anymore comparable and consistent. Different kind of hierarchies and categories used in an organi-

zation can exist, but those need to be clear from what viewpoint they are created. (Laursen & Thorlund 2010, 100-101).

3.4.6 Dimensional data modeling

Operational databases and data warehouses have different purposes. Online transactional processing support business execution; data warehouses on the other hand are created for analyzing and evaluating business operations across the company. Entity relationship modeling and 3rd normal form (3NF) data modeling supports OLTP system creation and major goal of it is to reduce data redundancy in relational database systems for data entry (Berson & Dubov 2012, 171). This relational database modeling approach was developed and introduced already in 70s' by E.F. Codd (Codd E.F 1970, 377-387).

If enterprise data models are created illustrating the various business and process integrations between data entities in a normalized way, these data models can include hundreds or thousands of data entities with complex relationships to each other. In a data warehouse or even in smaller data mart environment relational normalized modeling approach is not necessarily an optimal way to model business intelligence data for reporting and analytics purposes since the retrieval of data using 3NF data model schema is not the best one from the performance perspective. Therefore dimensional modeling is used for business intelligence reporting and analytics solutions. (Corr & Stagnitto 2012, 4-6).

In dimensional modeling, data is represented based on business events of measurable things (facts) and surrounding descriptions (dimensions) which can be used to filter and group the measurement figures from different angles (figure 7). The purpose of the dimensional modeling is to keep table joins as short as possible and thus maximizing performance of data queries. Data can be denormalized in a way that data is organized efficiently for queries. This is a different design principle compared to OLTP design and optimizing transaction processing in data entry process. (Corr & Stagnitto 2012, 7-10).

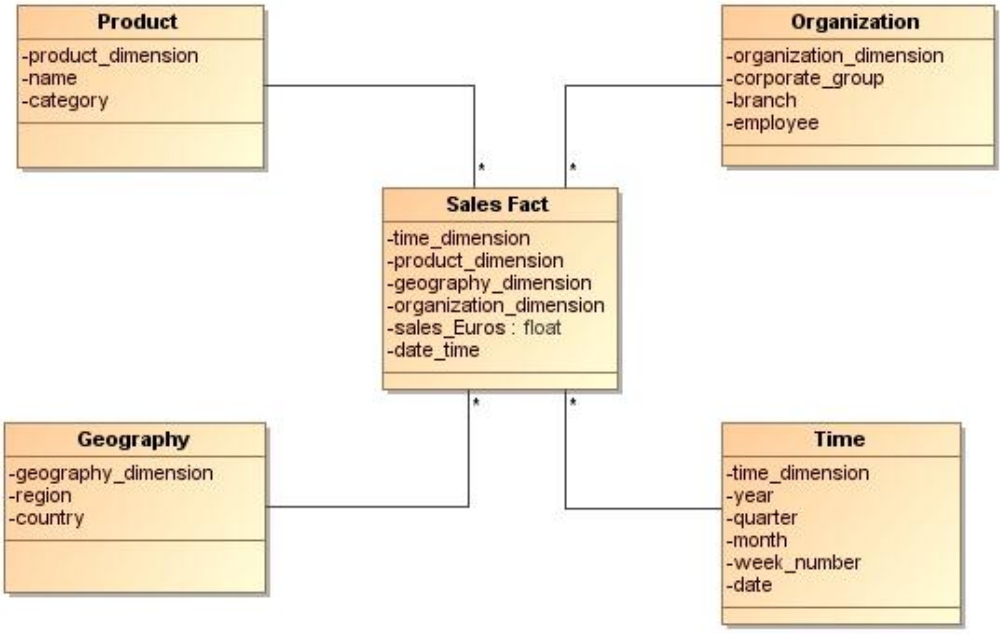


Figure 7: Dimensional data model example

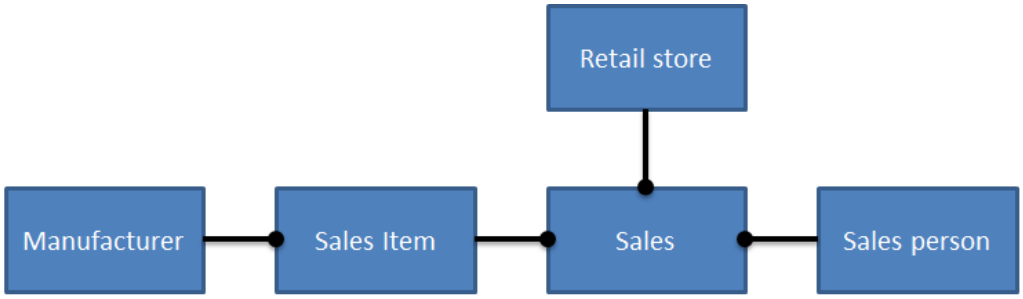
3.4.7 Business intelligence and master data modeling complexity

As explained in chapter 3.4.6, dimensional modeling is used many times for data mart or data warehouse implementations for business intelligence applications. The reason for this can be explained using social science theories and studies of so called Small World problem introduced by Stanley Milgram in 1967 (Milgram 1967, 61-67). In this study, Milgram introduces a well-known phenomenon and phrase of "how small world it is"; that is, concentrating on the occurrence of what is the probability that two persons in a world would know each other – which is naturally pretty low, but it can still happen (making the world small). The question becomes more interesting when considering the options that if persons X and Y do not know each other (which is very likely) but if person Z does know X and Y. By continuing this kind of thinking Milgram depicted a theory of how many intermediate links are needed in a certain population before X and Y can be linked. This is the basis for Robert Hillard to suggest that complexities of data models should be evaluated using Milgram's network theory of vertex (data entity), average number of connections to entities (relationship) and number of entities in per vertices to analyze the complexity of data model (Hillard 2012).

Regarding business intelligence reporting and analytics, master data is needed to make transactional figures and numbers understandable and meaningful. Master data repre-

sents the viewpoints around the facts of business events showing who, when, what, where, how and why something happened. Together they show facts representing business process activity (verbs) in dimensions of classifications (nouns). (Corr & Stagnitto 2012, 44). Depending on how many of different kind of dimensions there are, these dimensions as relationships to transactional facts can be illustrated as a data model. Many times the relationship between data entities is as important to the business as is the content of the data entities. What creates a challenge from business intelligence creation perspective is how to manage the complexity of a business data model. Increasing level of relationships starts to be not just hard to implement but also to understand by the business end users, which makes reviewing and understanding the business data model even more difficult.

From the mathematical perspective, data model is nothing but a graph showing set of connected nodes as a network. Complexity of a data model can be evaluated by calculating three metrics: average degree, average geodesic distance and maximum geodesic distance (figure 8). When calculating these values Hillard (2012) suggests that consideration needs to be done between the number of relationship divided by the number of data entities; if the ratio is lower than one (1) then in general more of the information is held in the content. If the ratio is greater than one (1) then the majority of the information is about the relationships. The theory also suggests that physical database model should not exceed of average geodesic distance and average degree of four (4) and should aim for a maximum geodesic distance of approximately 10. If the model exceeds these limits, implementing the data model as a database creates a testing challenge and needed competence to test the queries might require substantial expertise level and also needed time to test the queries thoroughly (Hillard 2012; Berson & Dubov 2011, 170). Since conceptual data models should in general be more simplistic than physical data models, it is quite safe to assume the same rule should relate to conceptual data models as well. If they are too complex, it might has also bring potential data quality risk; if the business users as a validation group can't understand the model, verification of the data model content and relationships correctness becomes a quality validation problem.



Number of entities (order): 5
Number of relationships (size): 4
Average number of connections per node: (1+2+3+1+1)/5=1.6
Average geodesic distance of all entity pairs: (1+2+3+3+1+2+2+1+1+2)/10=1.8
Maximum number of relationships needed to traverse between the two most remote entities in the model: 3

Figure 8: Data model complexity calculation method example. (based on Hillard 2012).

In a star schema dimensional model having N dimensions, the number of entities (order) is N+1 (N dimensional tables and the fact table), and the number of relationships (size) is N leading into the average geodesic distance being (1*N + 2*N*(N-1)/2)/[(N+1)*N/2] = 2. Since the assumption for star model being useful is that the fact table is much larger volume-wise than the dimensional tables, it is recommendable to keep dimensions denormalized because the data redundancy in fact tables does not oversize the amount of data since the fact tables represent the largest volume of data anyway. But, if this is not the case and the dimensional data becomes as large or even larger than the fact table data, hybrid approaches should be discovered, or consideration of splitting down the overall business questions in separate business intelligence subject areas in more manageable pieces. (Berson & Dubov 2011, 167-174).

Although star schema is beneficial as a dimensional data model to represent and answer specific business questions and to evaluate business events through many dimensional aspects, it has still some drawbacks. If the business requirements are not stable but tend to change rapidly, or if the user community of a star schema starts to expand wider than that was originally estimated, problems start to proliferate. If the data granularity varies across different user communities and across an organization, the data in different star schemas needs to be arranged in the lowest level of granularity for integration reasons. This in turn makes the usage of star schema concept theory practi-

cally useless. In these kinds of situations data warehousing approach keeping data in 3rd normal relational form and in detailed level, and building a data hub as a data warehouse serving other business area specific data marts could be more valid approach. The business context and requirements dictates what the suitable architectural pattern is, and needs to be validated openly inside a business and IT organization. (Inmon et al. 2008, 18-21).

3.4.8 Linking concepts, information and knowledge together with ontology

When business concepts are shared inside an organization that doesn't mean that the ontology is in shape. In information science, ontology means definition of concepts and their relationships to each other, which can be in a business environment very context-specific (Wikipedia 2012_3). Tom Gruber defines ontology as an "explicit specification of a conceptualization" (Gruber 1993, 199). From the business perspective, the key words in this definition are not only 'conceptualization' but also the 'explicit specification'. In the business environment first step is to share concepts explicitly inside an organization. Having a common capability for knowledge sharing requires also that common ontology for the company exists. This means that if concepts are shared but they are not commonly agreed; or if knowledge is just referring to conceptualization but it is not taken into use; or if a set of concepts is only shared and used inside one specific are (like an application or a part of an organizational system) but not shared for a business domain across applications, ontology is still missing (Dillon, Chang, Hadzic & Wongthongtham 2008, 7). Having consensus of interpretation of concepts and understanding of them in the context of a business domain or across domains are crucial for ontology existence.

For an enterprise, amount of the needed sharable data and consensus of its usage across in an organization is one the key topics when utilizing and linking data across multiple business domains. This becomes especially important in the enterprise data warehouse environment when common interchangeable knowledge sharing and analytics is in use (Davenport & Harris 2007, 185). Having a set of commonly used and agreed concepts is a fundamental requirement of having a possibility to use automated tools like ICT systems for data transformations and integrations. When concepts and

conceptual models are transformed into logical and physical data models and related supporting tools having agreement of common semantics and ontology across business domains, transforming data for business purposes becomes an easier task compared to situation there's no agreement on the ontology. If the ontological linkage is missing, this normally means time-consuming and error-prone human interactions and manual work in transformation, extracting, sending and receiving data between the ICT systems and databases. (Dillon et al. 2008, 7-8).

It is also important to understand the difference between ontology, concept and information linkage to knowledge creation: ontology defines agreed and shared concepts and terms which are used to represent knowledge. Concepts (and conceptual models) link information and data together giving a meaning and a definition for contextual data representation and thus are actual ground facts for information sharing. Ontology plays an important role by defining the vocabulary used to compose complex expressions of a business operating environment. (Gruber 1993, 2-3).

3.5 Insight creation

Insight means about understanding how different actions have cause and effect in a specific context. This can be done through introspection, observations, deductions and perceptions of business environment and about the business organization itself. Insight is a human capability to really learn not only what happened but also to really understand the root causes of a phenomenon and end results of human behavioral actions. (Davenport et al. 2010, 6-7).

Business organizations use different kind of methods and approaches to learn how they are advancing or making the business. The key is to first define what the business questions that needs to be answered are. This should lead and to be reflected also in the IT tool development and making focus and priority selections of the development efforts. Defining the right questions or using e.g. data mining techniques to find new better business questions is a step forward having analytical approach and to become an analytical fact-based driven company.

Business questions can be organized in two categories of time frame and innovation. Time frame defines whether the business questions are looking in the past, in the present or in the future. Innovation aspect defines whether the organization is working on known facts or if it is creating of new insight. Depending on the business need and type of questions, different kind of reporting and analysis needs can arise. Sometimes there are no time for data collection phase and deep analysis; business decision for rapidly changing market situations might need to be done immediately by the management. But, if there is a chance to prepare for these kind of situations, business management should preserve some time to find the right questions and be prepared to find answers to them with the business analytics (Davenport et al. 2010, 10-11).

3.5.1 Knowledge creation

Knowledge cannot be created without individual persons and thus an organizational knowledge creation is based on human beings using tacit and explicit information and sharing a common ontological view on top of the data. This can be seen to happen in four different cycles: socialization, externalization, combination and internalization phases. In the socialization phase people share tacit information with each other (like in brainstorming sessions). Socialization happens internally in the organizations or with external parties as well (like customers). In the externalization tacit knowledge is defined as explicit concepts; this is done by defining conceptual models, analogies, hypotheses and metaphors. Explicit information combination is about using other explicit information where individuals exchange and combine information using tools like databases, business and information models to operational plans, use computerized network communication capabilities for information finding and sharing, and find other knowledge like educational training as well. In the process of internalization explicit data becomes to tacit information again by using and doing things in practice and using explicit data for creating user stories, writing documentations or other presentations to be shared in the business community (Nonaka & Takeuchi 1995, 56-62).

When new business questions arise or new opportunities are created in this cyclic event of knowledge creation, ontology and conceptualization becomes very important vehicle to share the knowledge and create new knowledge. With the explicit data, process

of data mining can be used to explore large amount of existing data to discover new patterns and business rules which are useful to business. This can also be used to expand or modify existing ontologies of business organization operations and to find new competitive advantages for it. (Linoff & Berry 2011, 1-4).

3.5.2 Reporting and insight differentiation

As defined in chapter 3.5, Davenport, Harris and Morison (Davenport & et al.. 2010, 6-8) divide analytics and related business questions in two levels: time frame and innovation levels (figure 9). Question that answers a basic question "what happened" are managed by developing reporting capabilities. This viewpoint is about looking in the past. The next time frame question is to look on present things by answering to a question "what is happening now". These kinds of questions can be handled by generating e.g. alerts or warning systems; for example, if something is happening in a way it is out of the normal situation pattern, alerts can be created and send it to the manager being responsible of such a process. Using some extrapolation patterns and calculation rules it is also possible to predict and answer to a question "what will happen next" in the future. All of these kinds of situations are more or less information sharing and using information in different kind of time frame viewpoints. Using the business information in this kind of way is in fact answering to a question what has happened or will happen if the circumstances are not going to be changed. The problem of this kind of reporting or analytics usage is that information does not explain why the things have happened as they have. (Davenport & et al. 2010, 6-8). For example, sales report from the past quarter showing sales revenue status does not explain why the sales figure as it is; you can actually stare the sales figures "till the cows come home" (Video of Parmenter, 2011), but you can't say based on the revenue why it is as it is and how to improve it. More explanatory data and methods are needed to create new information and new insight based on the data.

	Past	Present	Future
Information	What happened? (reporting)	What is happening? (alerts)	What will happen? (extrapolation)
Insight	How and why it happened? (business modeling and analysis)	What's the next best action? (recommendation paths)	What's the best/worst to happen? (prediction, optimization, simulation)

Figure 9: Key questions addressed by analytics. (Davenport, Harris & Morison 2010)

To answer questions like "how and why things happened", "what's should we do next" or "what's the best or worse that can happen" requires different tools and techniques rather than just reporting the plain figures of the past. More explanatory angles to business are needed as well as different kinds of statistical analysis methods and models. For example, if company's customers are not satisfied with the supplier's product offering, this will certainly impact to the sales. The faster you realize this, measure it and understand the root causes as part of customer satisfaction indicators, the more you can predict the future sales. (Davenport & et al. 2010, 137-140).

3.5.3 Reporting and analytics capability creation

Different kind of questions can be addressed depending on the time horizon based on the business need. If information sharing is enough or if more complicated analysis methods are needed, it is a matter of advanced business analytics. Another aspect to reporting and analytics creation is the urgency of the reports and analysis needed. If it is good enough that information is just represented, no hypothesis tests or analyzes are needed to be done. Showing plain figures of sales, for instance, is then enough. This means that the interpretation of this information is left to the information user. Many times these kind of reporting solutions are created quite easily, and then their creation can be automated as well as many times the delivery process of the reports sharing the information. This is a typical IT department approach for the solution creation. Different kind of levels in reporting (operational vs. strategic reports) might require that data is populated in a same data warehouse to support e.g. daily and monthly sales report-

ing. This becomes an important approach especially when the data quality and one set of baseline data is a common concern to make the reports comparable and balanced. (Laursen & Thorlund 2010, 115-116).

One of the data warehouse paradigms has been to choose between Ralph Kimball dimensional data mart development and Bill Inmon data warehouse development ideas. Kimball believes that data warehouse is a conglomerate of all data marts in an enterprise, and having conformed data dimensions makes different data marts and different fact tables comparable to each other. Inmon principles define that data warehouse (especially enterprise data warehouse) is a single strategic place for data sourcing that companies should construct for their business intelligence purposes. In this kind of data warehouse, data would be stored and managed in 3rd normal form, which can then be provided for other data marts sourcing the data from this common warehouse. Both design paradigms are possible: it is a question of how business organizations sees their position in data governance and what is their attitude towards data management going forward. (Serra 2012; Inmon & et al. 2008, 15-21; Kimball R. 2012).

If the purpose of business intelligence creation and data is seen as a strategic asset, data warehousing by Inmon might be the preferred way; if the attitude of data analysis is more on the departmental side, multiple data mart creation work and Kimball approach might be chosen (Serra 2012). Common challenge for both approaches comes in defining and agreeing what is conformed and what are the common definitions of different dimensions since different departments inside one company can have different semantics regarding the dimensions, which is a political challenge for a company to tackle. (Corr & Stagnitto 2012, 98-99).

3.6 Data quality

Today most of the organizations depend heavily on data. This happens generally in two ways: standard business operations are executed as transactions of business events, and supporting activities are managed before and after the execution. Data is used to run and improve the business execution and to reach business targets of an organization. Since data is also a strategic asset to differentiate company from its competitors, there

have to be processes that are established to ensure that data available has sufficient quality to meet business operational and management targets and needs. (Loshin 2011, 1).

When talking about data quality and data quality improvements, it is important to notice that the data quality cannot be detached from the context where data is going to be used as information and for knowledge creation. In analytical decision making process, using business intelligence solutions and different information sources data doesn't need to be nearly as perfect as it is required in transactional event recording environment (e.g. billing and invoicing). Naturally understanding of what is the needed level of data quality has to be considered beforehand, and what is the current state after information analysis activities. For example, if customer address is outdated in the transactional contact center system, that is annoying and sometimes even a severe problem for re-contacting the customer afterwards. For customer relationship analytics, this is necessarily not a problem at all. Having the same data quality requirements for both analytical and transactional systems is far from optimal data quality management target. (Davenport et al. 2010, 31-32).

3.6.1 Definition of quality

Quality can be defined in many ways depending on the context quality is measured or experienced. In short, quality can be seen as "fitness for use" (Cappiello, Francalaci & Pernici 2004, 68). Quality frameworks like TQM consider quality as continuous improvement of processes, products and organizational systems needed for running business operations to meet customer expectations. Six Sigma framework looks similarly how to improve systematically business processes where the target is to reduce the fluctuation of product quality and making changes into the process and capabilities in a manner that the quality is in the acceptable quality tolerance. (Wikipedia 2012_e).

Making a similar quality control as defined in TQM or Six Sigma is relevant in the business intelligence data management area as well. The idea is to ensure and control that different fact (business measures) can be viewed from different angles (data dimensions) and that the data is in an acceptable quality level. Information relevance re-

garding the data usage situation, the ability of the end user to use and understand data correctly and to understand if the usage situation itself is understood correctly is highly contextually driven (Watts, Shankaranarayanan & Even 2009, 202-203). This is why information quality is hand in hand with the usage or process quality as well, and needs to be considered respectively in that context. The same applies also in improvement activities of data quality since information that is having acceptable quality for certain decision making or operational usage may be perceived to be of poor quality for another decision or operational situation (Cappiello et al. 2009, 72).

3.6.2 Dimensions of data quality

Data quality can be considered from different angles and dimensions. These dimensions can be first divided in two sections: intrinsic and contextual quality dimensions (figure 10). In intrinsic dimension, data can be analyzed based on how accurate it is, how data is sourced and what is the lineage of data, how well it is consistent structurally as well as from the semantic perspective. Contextual dimensions cover data quality aspects of completeness, consistency and currency, timeliness, reasonableness and identifiability of data. These dimensions also comprise key characteristic metrics as a baseline in data quality assessment. It is important to have criteria for each dimension whether the data quality is in adequate level or not – this is of course a matter of a particular organization to define and decide as well as conformance threshold defining the needed level of conformation of data. This is a task that needs to be done according to business needs and usage. (Loshin 2011, 129-146).

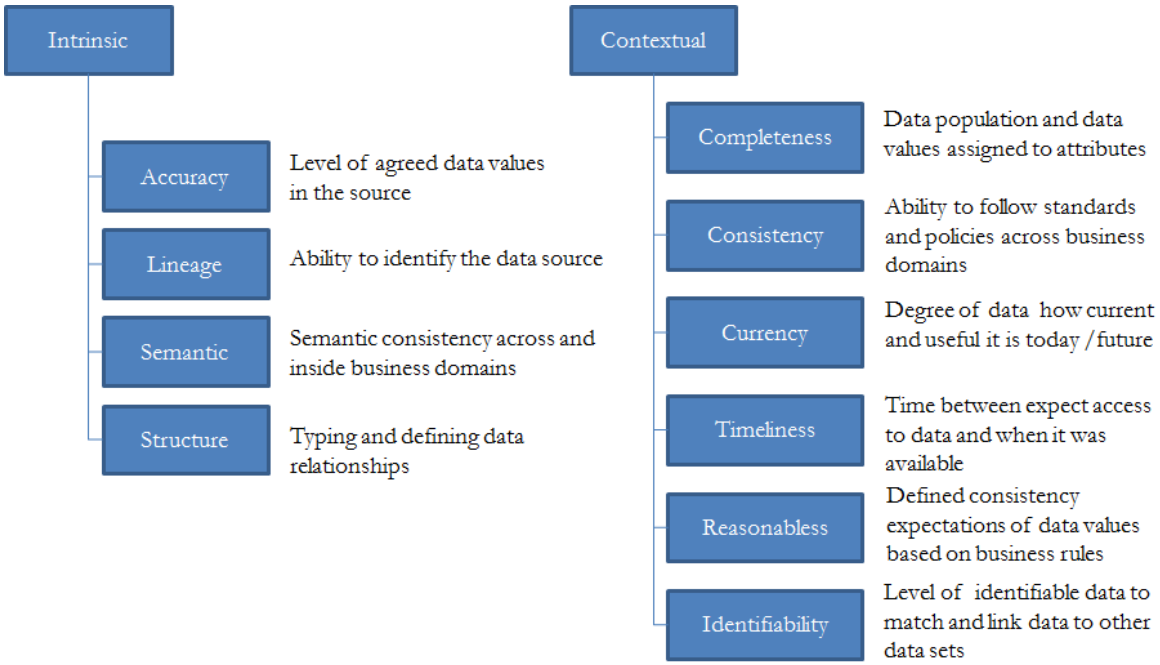


Figure 10: Data quality dimensions. (Loshin 2011)

Madnick, Wang, Yang and Zhu (2009, 6-7) highlights the multidisciplinary role of data quality covering a wide range of topics. They divide data quality impacts in five subcategories: 1) application area, 2) performance, cost and benefit operations 3) IT management, 4) organizational change and processes and 5) strategy and policy. Failure in converting data into actionable information is common explanation of why information systems containing lots of data sometimes fail to satisfy information needs. From this angle, information quality can be categorized in these five categories: 1) intrinsic quality of information, 2) information accessibility 3) contextual quality of information 4) representational quality of information and finally 5) security and control of information. (Alter, 2009, 159-168).

According to Lee (2004, 99), "data activities, as with other activities, are influenced by contexts". The same viewpoint is taken by Watts, Shankaranarayanan and Even (2009, 202-203). Understanding the context is needed when analyzing data quality across processes and activities. Since this might create some significant changes for the organization activities or operations, impact to business processes needs to be analyzed. Change can become as an improvement only if the change is implemented in real-life processes (Laamanen & Tinnilä, 2009, 39). This is in sync with practice-oriented case study research methodology goals presented by Dul and Hak (2008).

3.6.3 Data quality measurement, targets and linkage to business performance indicators

Before setting any data quality targets and related metrics for it one must put focus on the design of producing and generating data. Not all data is created for analytical and business intelligence purposes, so some transformation might be needed to adjust data to fit for the purpose. (Wand & Wang 1996, 87-89).

Data quality can be considered also from two theoretical approaches: communication theory and information economics perspective. In communication theory, signaling in a noisy channel can result difference between what the message was when it was send and what was it when it was received (Shannon 2001, 3-4). On the other hand, information economics theory focuses more on information usage. When using information economics approach it is possible to compare what information sources are most beneficial for a person or organization.

Although communication and information economics theories provide formal treatments of communication measurement, they ignore how the design of an information system and information usage situations affect to the data quality and how this should be measured. The value of information is in the terms of the outcomes a person can act upon the information. If the outcomes are erroneous and the errors are happening statistically outside of the range of an acceptable tolerance, there is a good business reason to investigate also if the errors are happening because of the wrong information, or, wrong actions are made by right information. This is also a reason why data quality cannot be measured only by using mathematical perspective to data but also from the ontological perspective how it is interpreted. For knowledge creation success ontology is an important agreement of an organization to agree with the meanings and semantics. Having no agreement means there is no target; and from the data quality perspective this is what is needed. Therefore, data quality dimensions and their data quality targets have to be defined in the context of how the organization wants to set its operational targets. (Wand & Wang 1996, 87-89).

Data quality targets and metrics have a close relationship to organizational performance and result indicators, especially those which are the most important for the organization as key performance/result indicators (figure 11). If business performance is measured based on some key result information entities (revenue and profit, for instance) which cannot be trusted because of the fluctuations in different data quality dimensions, that result performance indicator becomes erroneous. This means that the result indicator is not valid to give actionable guidance for individuals or for the organization. If the data quality target is not known beforehand, or data quality as a topic is totally ignored, process of producing data for decision support is not in control and is not manageable either. This may have severe consequences for the company's performance measurement and KPI/KRI reliability. (Masayna, Koronios, Gao & Gendron. 2007, 1377-1383).

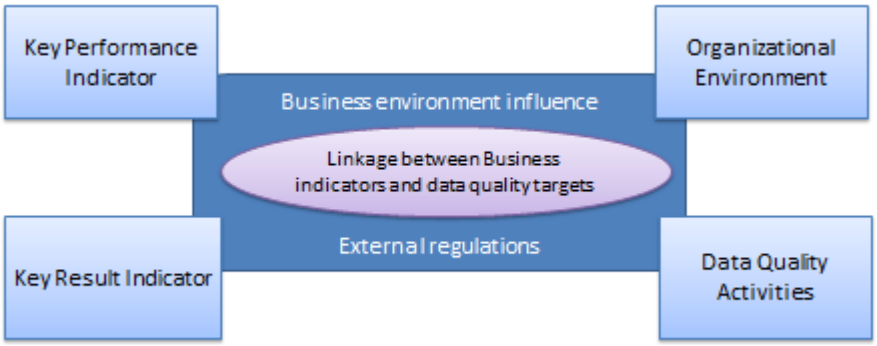


Figure 11: Establishing links between DQ initiatives and organizational KPIs and KRIs. (based on preliminary model of Masayana & et al. 2007, 1382)

Goals of a company can be different when looking different parts of the organization. Any business organization strives to make profit, and this is of course one of the key outcome results to be measured also internally how well an organization can execute this target. There can be other goals as well, like IT goals, process goals or other operational excellence goals as an example. What is important to realize is that measurement is not the same thing as counting. Estimating and counting is sometimes mixed in business; to estimate how many of consumers are interested in company's products shouldn't be considered as a counting exercise. For estimation, measurement can also be done based on small amount of data and with a data that is not state of the art quali-

ty. (Hubbard 2010, 22-26) Still, data quality plays an important role in business intelligence. The level of required quality varies depending on the context of analytical methods or how performance is measured. This applies especially to key performance indicator level data; e.g. the data quality requirements and what is required level of accuracy and trustworthiness in business process improvement measurement area can be quite different compared to company's official financial profitability calculations.

Performance measurement can be accomplished in many ways, and it can be represented in many ways as well. Before measuring anything, and before starting to collect information for the measurement it is important to define why the measurement is important: what is the business question company is trying to get an answer (Hubbard 2010, 41-42). This means that business objectives must be translated to outcome measurement and performance indicators. Data needed to be used in calculations of those indicators needs to be valid, compliant and the meaning of the data needs to be well known and defined before using it for calculation or analysis purposes. (Masayna et al. 2007, 1376-1379).

One easy way to increase success rate of resolving data quality issues in performance measurement is to focus on metrics that has some real business value. This means that validation of metrics whether they are vanity metrics or actionable metrics needs to be evaluated first; for example, reports showing metrics which are not actionable do not create business value (Ries 2011, 143-144). Data collected for the vanity metrics creation is sometimes easier to do and therefore might gain popularity in the data gathering process and reporting area which should be actually stopped. Parmenter (2010, 23) actually claims that "many management reports are not management tools but merely memorandum of information". The point here is that monthly reporting needs to be combined with weekly and daily view reporting view with actionable metrics in place to show performance and result indicators leading into actions; quarterly and monthly reporting does not do that (or the lead time from the measurement period to actions is too long).

Combining different time frame or innovation views together leads into a requirement to make the figures comparable. This might mean that data needs to be cleansed and

transformed to same place for reporting, and required data semantics reflecting business rules needs to be managed to able combined reporting view in different time frames (Laursen & Thorlund 2010, 170-174). Creating companywide metrics from the multiple data sources is possible but the tendency is that they just create multiple truths from multiple data sources and the energy of an organization might go in quarrels which figures generated by IT reporting system or department are better than others (Davenport & Harris 2007, 166-167). Despite of the importance of having good quality data for the business, one must avoid a pitfall of perfectness. Data management and quality improvement ideas just for sake of its own and expecting high quality targets everywhere is a killing approach for startups for embedding analytics in business use. Many highly analytical capable companies still have incomplete data although they have perfect data governance structures and processes established. (Davenport et al. 2010, 133). It is the usage of data and understanding the decision supported metrics importance that should guide these quality improvements across the business organization. Too low and too high quality should be compared with a cost to value (Hubbard 2010, 107-108). The most important thing is to understand correctly the level of consistency expectations from the business side towards quality requirements (Hubbard 2010, 281). This should lead also data quality initiatives both in the business and in ICT side of a company.

3.6.4 Statistical process control in data quality management

Statistical process control (SPC) is a method of quality control that uses statistical analysis and methods as the name says. It is about monitoring the execution process and controlling it. Control charts, also known as process-behavior charts or Shewart charts named after the inventor Walter Shewart of SPC in early 1920s, can be used to determine if the business process is in a state of statistical control, meaning, the variance of the process outcome is in the acceptable tolerance. For data quality management, the manageable process can be any information process that creates or uses business information. (Wikipedia 2012_d).

To be able to statistically control the process, control points with quantifiable measurement are needed. This can be managed by using control charts. Control chart has

the values of a time series, or sample series if sampling is used, of needed data quality dimension metric. For example, if the goal is to measure how much of data entered in a system is non-conformant against specified data quality rules, sample measurement can be taken and calculation of how many of data points are non-conforming by using binomial distribution as an assumption if the process is constant. If this will not be the case, there is a room for improvement of the process. (Loshin 2011, 99-109).

The goal of statistically controlled process management is to create stability and predictability. As long the data points and data quality measurement regarding these data points are in the control limits (inside the required tolerance), the process producing data is stable. If the data is critical for the organization, control charts can be followed as data quality scorecards. What should followed in this scorecard should be reflected from the business scorecard performance indicators so that the data needed to calculate business performance is consider as candidates for SPC process of data. (Loshin 2011, 109-113). Control method for data governance can be based on the same approach as it is used in embedded business analytics of an organization bringing thus data management together with business management (Davenport et al. 2010, 128-129).

3.6.5 Data governance

Governance is about management of people to reach defined goals and targets. Data governance is a specific subject area that needs to be handled as part of other business operations and management activities. Data governance is management and leadership process focusing that the needed data for business operations as well as for business intelligence is in place, meaning, that the data needed in business is available and it fulfills the needed defined data quality targets. This applies also to data security policies, data standards, privacy and accessibility rules. In this way, data governance is not just the IT department's task to follow since data management is involved today in everything organizations do; on the other hand if there are no instances looking after it, it many times means nobody is responsible of it. Therefore companies having analytical aspirations and having a need and willingness to invest on business intelligence solu-

tions should nominate a special group of people to look after data governance as a special focus area. (Davenport et.al 2010, 35-36).

Data governance principles and execution need top level senior management leadership and commitment. Certain people in a company may have specific data governance roles. Executive decision makers are responsible of target setting what data is important for company's future and what data needs to be managed throughout the company. Most important data sets as data assets should be also defined by senior management since it will create need for efforts and resources to manage the data. (Davenport et al. 2010, 35-36).

Many organizations should nominate also people in the role of data owners or stewards being responsible of particular types of data (e.g. customer, product, or financial data). These persons should be organizationally responsible and able to steer interpretation of data, its semantics, concepts and their relationship to each other, data quality requirements as discussed in chapter 3.6.2 including also information protection, privacy control and information life cycle operationally. These stewards and owners should have data governance responsibility as a professional role beside their normal everyday work. They should be also persons who support user community by collecting, collating and handling issues and problems with data, and are able to govern that other people follow those principles and rules that are needed to manage data for business usage. (Loshin 2011, 122-128).

Defining roles is a good starting point when implementing data governance in practice. In the same time, when roles and people working in those roles also have accountability and authority to act according the data governance rules, things start to happen in reality. Accomplishing data governance should always lead to actionable process control of data quality as well as an integration to other IT and business governance model execution. After all, data governance is not about just about IT or business governance but an alignment effort with those aspects, connected to overall enterprise's operational quality management frameworks. One of major challenges still is for globally operating companies to decide how to balance global vs. local aspirations of data management and quality controls and operating culture. This requires a companywide policy

and understanding of local circumstances towards global guidance. (Weber, Otto & Österle 2009, 14-23).

3.7 Improving business intelligence data quality capabilities

Depending on the analysis requirements and current data quality maturity level, different kind of data quality requirements and development needs can arise. The level of the analytical stage affects also how well an organization will focus, demand and drive for data quality improvements. Davenport, Harris and Morison (2010, 21-22) define the stages in five levels: in the lowest level, organization can be practically analytically impaired. This means, that the level of data integrity, timeliness and other data quality dimensions are not in the focus of company's doings. When the analytical capability needs increase step by step to localized analytics level (level 2), and furthermore when analytical aspirations expands to cover companywide aspect to use data across an organization towards fact-based decision making (level 3), more data quality topics come onto the agenda of the top management.

As the organization starts to see strategic benefits to use information and knowledge in a systematic manner on (level 4) and establishes enterprise data warehouse development programs to integrate internal and external data sources, data quality becomes a management topic. Further improvement of a company to become as an analytical competitor means it starts using analytical capabilities as a competitive advantage. This promotes establishing a business intelligence competence center as well as having enterprise wide data governance in place. It is very important to realize that when aspirations to use analytics increase, data management topics need more focus. This means that enterprise focus to use data is no longer only in functional silos but to use it across the company. Leadership, strategic targeting and analyst competence development becomes leading drivers also in capability development of a company (Davenport et al. 2010, 23-43).

3.8 Supporting business intelligence creation with semantic business information modeling and ontologies

Creating organizational knowledge and insight of business operations is sometimes a complicated process in which information is transformed to explicit and tacit knowledge. Knowledge, unlike information, is about people's beliefs and commitment. It is also about people's required action, which draws a line how much or to what extent knowledge is needed: no more knowledge is needed than the action requires. Depending on the organizational culture, this can be achieved individual level and many times quite easily; but it can and should also expand through the organization or even across other organizations (inter-organization knowledge). Knowledge shared across companies or even human cultures is dependent how people justify their beliefs. It is also context specific and relational, but it is a conscious decision of people to start to act for the community, and not just on the individual base (Nonaka & Takeuschi 1995, 56-59).

For knowledge creation, information is a commodity to create understanding, and having a meaning attached to the information is crucial. Ontology, based on the information and knowledge, is an agreement of an organization or other group of people about what knowledge is all about and what is the interpretation of concepts and objects in a business domain or across domains. (Dillon et al. 2008, 7). Without having agreement of concepts and semantics, it is difficult or sometimes impossible to define what the organizational knowledge is, and what kind of knowledge is needed for business decision making, operations and analytics. This relates also to the willingness to share and continue sharing this knowledge as part of an organizational culture.

Increasing the validity and coverage of the business information to business users, and to understand and share knowledge based on the common semantics and ontology is important also for business intelligence creation. If the business users would have better understanding of the semantics and ontology around data warehouses and other data sources, retrieval and browsing and validating the data would be easier to accomplish. Having both data requirements described as conceptual data models, and having also a presentation of what has been already stored in the data warehouses and data-

bases in conceptual data models would bring benefits to business users by having the possibility to find and compare the right data sets for further investigations without having deep knowledge and technical skills of data warehouse implementations, as illustrated in figure 12. (Spahn, Kleb, Grimm & Scheidl 2008, 1-12; Hoberman & et al. 2009, 119-124).

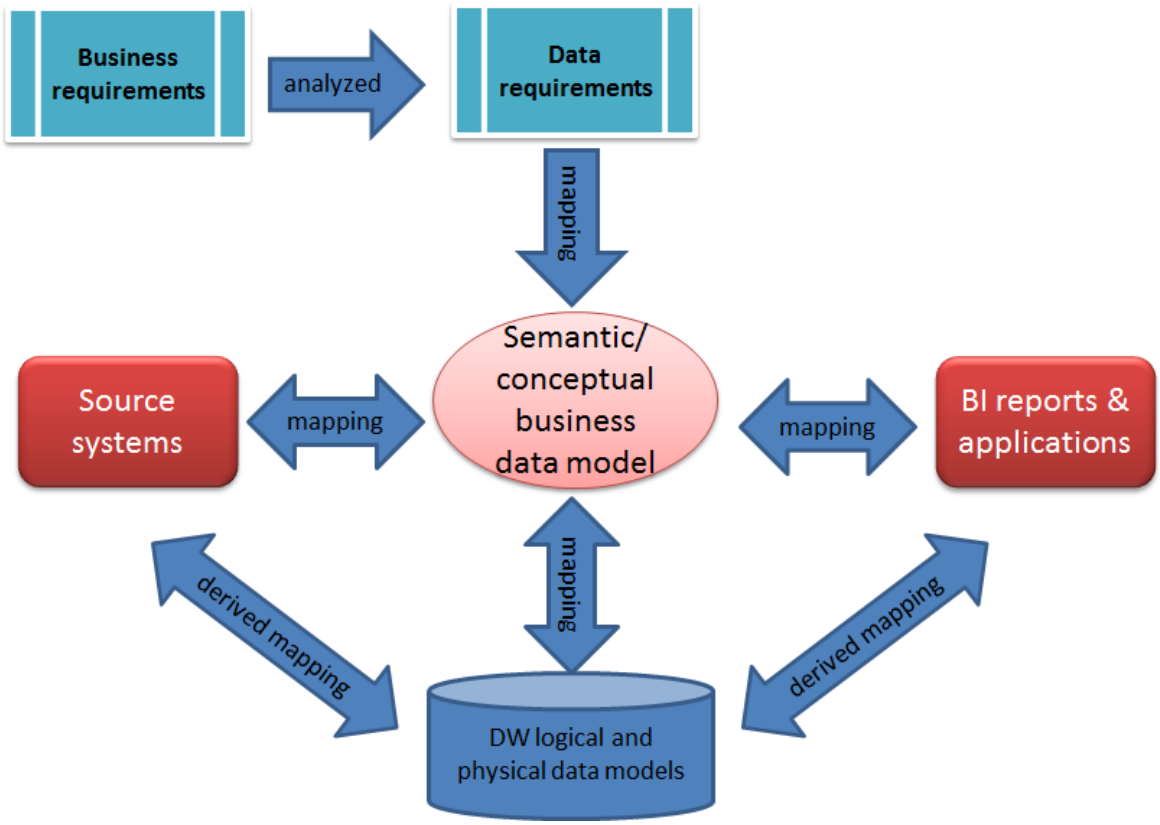


Figure 12: Business semantics and data warehousing. (based on Preibe, Reisser & Hoang 2011).

3.9 Summary of theoretical framework

All the things explained and described in this theoretical framework can and should be brought together as an operational framework to enable business intelligence capability development and having quality aspect included and kept in mind. Data modeling in different levels, starting from conceptual models through logical, dimensional and physical modeling shows the design of the needed construction of information needed by the business organization. This design can then be used when creating business intelligence capabilities to serve business decision making, operations and performance measurement against business targets. Dimensional modeling is an important model in

business intelligence environment since it shows visually the linkage between needed business measurement facts (transactional data) with dimensional data (master and metadata).

Using dimensional model in the discussions of needed data quality requirement with the business management makes it easier to them to realize what kind of information management concerns there might be, and what kind of actions are needed also to be managed regarding data integration. This is a good way also to illustrate concepts as well since the dimensional model is easy to understand for business users. Relational style of conceptual data model as a diagram should not exceed the average geodesic distance of four and maximum geodesic distance of ten at least when considering to representing them to business stakeholders. Exceeding these limits might also have impact on reviewing and validating these semantic data models from the data quality perspective as well; if the model is not understandable, validation of it becomes difficult and thus leading into possible quality problems already in the design phase. Answer for enhancing the communications of data model in this kind of situations would then be in splitting the model in more manageable pieces.

As part of operational quality control, business intelligence capabilities as well as related master, metadata incl. referential data, and transactional data must be governed in a manner it fulfills business organization's information, knowledge and insight creation need to conduct and manage its business targets (figure 13).

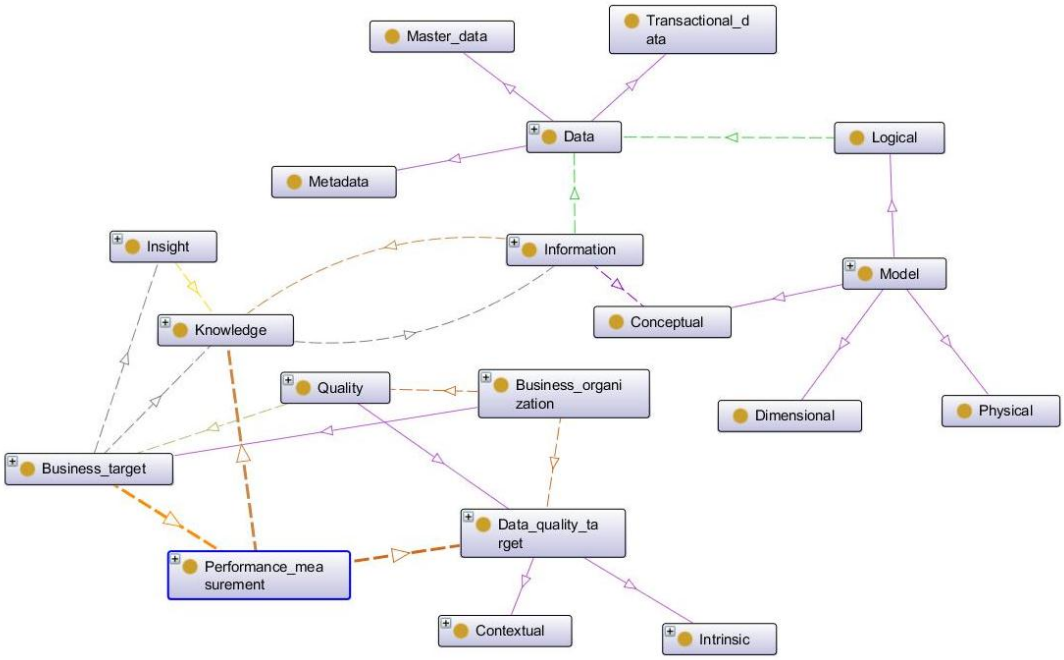


Figure 13: High level presentation of theoretical framework as ontology in OWL graph presentation

In performance measurement, business results carried out by business organization operations are targeted and measured by management. Depending on the viewpoint, measurement can be result oriented and shown as result indicators (like revenue, profit, customer satisfaction percentage etc.), or measurement can be about explaining success factors influencing results as performance indicators (like lead time to market, service success rate or channel inventory turnover time). Some of these indicators (but not all of them) can be considered as organization's key indicators, looking in the past, present or to the future. New information and knowledge as insight can be created based on existing data and performance measurement by utilizing new kind of business and data models. Finding new business models business organization can analyze, find and learn new opportunities and ideas, share that as knowledge and adjust its business targets by setting new targets based on the new findings and insight (figure 14).

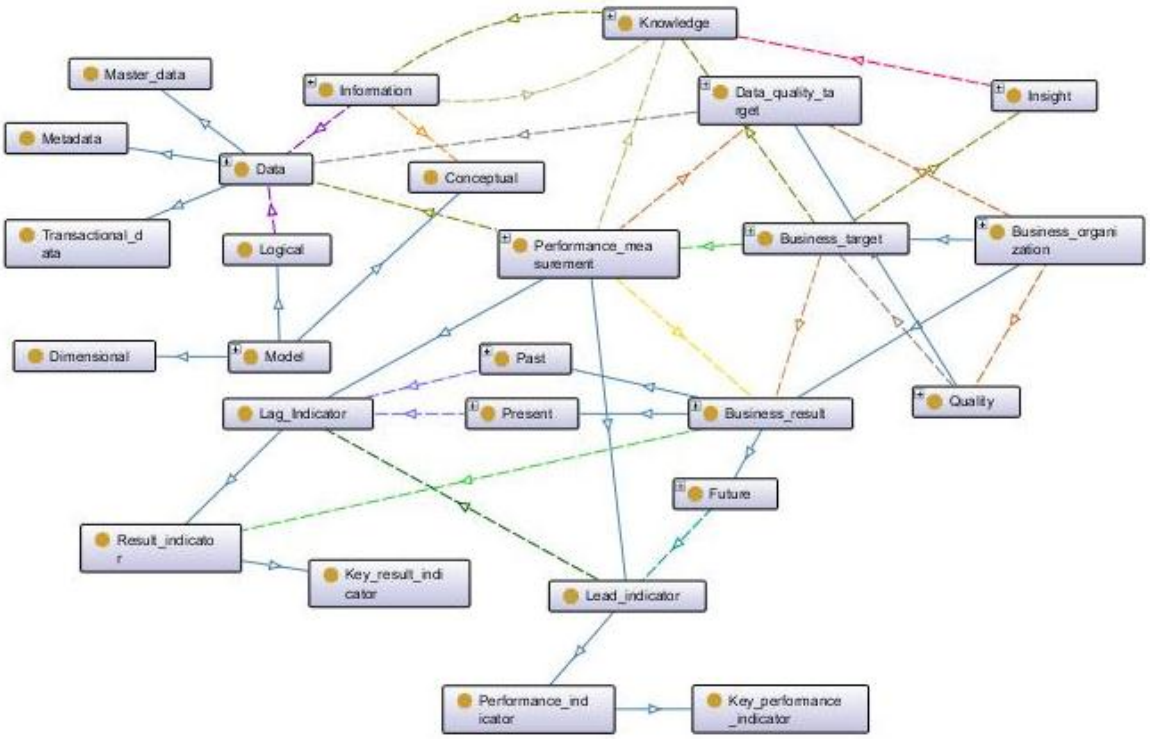


Figure 14: Theoretical framework as ontology in OWL graph presentation including data, information, knowledge and insight linkage to with performance measurement and indicators with business target setting and results

When data quality targets are linked as part of organization quality management, linkage to data and information becomes more operational and transparent. This can also lead into more agile way to operate since the data quality improvement areas become linked to business targets making both business and IT organizations to focus on topics that matters the most (figure 15).

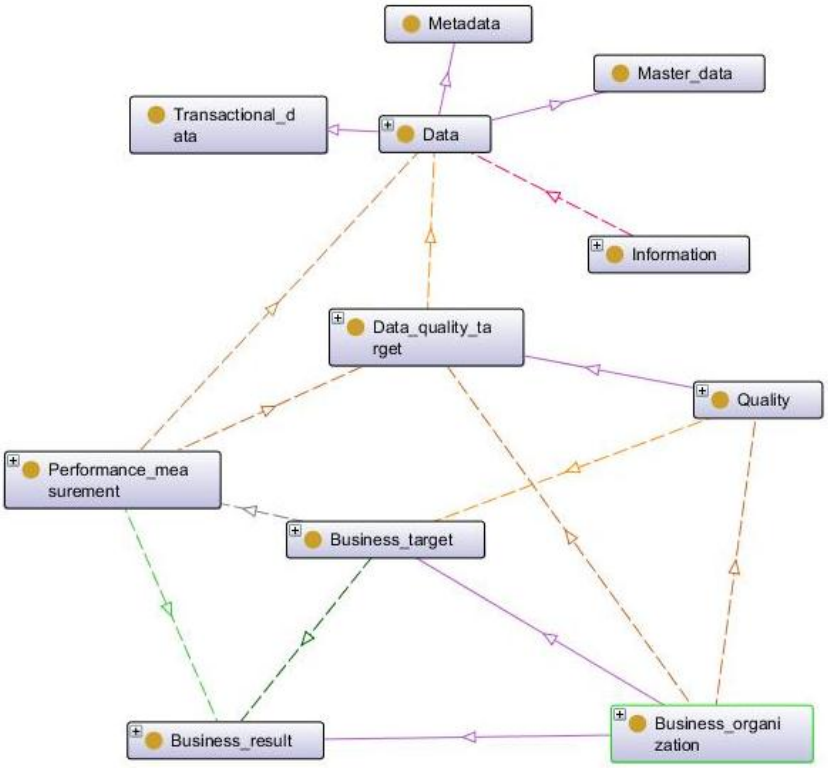


Figure 15: Business driven performance measurement and role of data quality in OWL graph presentation

The theoretical framework itself can been constructed as a semantic RDF/OWL ontology model using Protégé tool (available from http://protege.stanford.edu/), which is included in appendix 2. The graphical presentations in this chapter (figures 13 to 15) are snapshots from the Protégé graph editor illustrating the main theoretical framework topics and concepts and their relationships between each other.

4 Results and findings

4.1 How better data semantics and ontology can improve business intelligence data quality?

To answer this research work's main question, the answer is simple: better data semantics and ontology improves business intelligence data quality by providing clear rules, understanding and definitions so that the data can be used and understood in a similar manner in business decision making process and analysis. As described in theoretical framework chapter 3.6, data quality plays an important role of business intelligence. If the data cannot be trusted, or, if the data definition semantic rules cannot be trusted,

the data itself cannot be trusted. Having a good quality of semantics is the first step in any organization to start data quality improvement. Data profiling analysis of multiple data sources can give beneficial improvement ideas, but they will just show the discrepancies and variations of the data. Examples presented in the classified empirical part of this study show that having clear definitions for the data plays a major role to solve data quality issues not only meaningful for the business intelligence but sometimes for the business itself. Therefore the answer for the research question and as a proposition is this: those main data entities that are important for the business measurement and analytics should be in the unambiguous semantic level so they do not cause harm for the business management by allowing misleading interpretations to happen.

Starting point where to find the key information definitions and to ensure semantic quality of information entities can be found when analyzing the key performance and result indicators and related information data sets that are needed to construct those key metrics. If all indicators are called as 'key', then the first thing is to define what is really 'key' and what is not regarding business performance measurement (Parmenter 2010, 8-12). When this is clearer, both business intelligence and analytical teams and competence centers, if exist, can start the definition work with the help of business stakeholders and also with IT experts. Those professionals having also data modeling experience and expertise are needed to define the common vocabulary around critical business information, to agree on the definitions and structure of the data company-wide, and to guide how to establish needed governance around the semantics and real life data to keep it constantly in sync and shape. The task sounds simple but it is not.

In the empirical case study of company X, company had created already data quality governance ideas and frameworks almost some ten years ago. The problem has been that business interest in to these ideas has not been in a very high level and they have not been very well understood always. IT driven data governance ideas have been adopted, supported and implemented in the past with various level of success and commitment. This has become problematic since business management has not always realized the importance of data quality management and hasn't considered that as part of a normal business work.

Agreeing on common semantics is a difficult task in large corporations. Data quality programs, MDM initiatives and other information governance activities tend to be difficult to implement if only IT unit and their departments are driving these activities. The main reason for this, based on several discussion and personal observations during the research work and even before that has shown that IT units focusing on data quality improvements are trying to make world a perfect place to live but are not able to link target of data quality improvement initiatives to business value targets and benefit creating actions. This is one of the finding that is aligned with Davenport, Harris & Morison (2011) analytical capability studies as well and regarding levels of analytical capabilities development. If the company is not an ultimate analytical data-driven company, or it has just started to become such a company and being in the beginning of its analytical journey, then it is obvious that IT driven data governance programs doesn't get required focus and buy-in from the business management. The importance of connecting data management and data quality initiatives to enterprise level targets, leadership and analytical capability development needs a holistic approach that has to be adopted by the top management and the need for the improvements should be invented and led by leadership team members. This takes always its own time. If the leadership commitment is missing, efforts of creating data management and governance development projects mostly fail.

One way to bring the topic more practical level would be to link data management and governance topics directly to company's KPI and KRI metric development in a way that required (good enough) data quality issues are covered as part of the performance management and capability creation, and not as a separate IT driven topic. Also, keeping in mind that since any data quality improvement exercises are multi-year projects and a learning journey for the whole company, this means that keeping focus on tangible, short-term benefit and proof-of-business-value creating projects will let the organization gradually learn and share the benefits of having good quality data. Getting results early encourages to learn more, and thus to find more benefits.

4.1.1 Role of conceptual data modeling in creating better data semantics and ontology

Modeling is an important way to represent a phenomenon, business events or objects as defined in chapter 3.4. It plays a major role in communicating concepts, their definitions and relationship in sync. It also simplifies the needed business information landscape by leaving out the details so the most important topics and things are only visible and which can be used for business stakeholder discussions and knowledge sharing sessions. Conceptual models give also a big picture which is important when business environment is changing rapidly. Having a broader look on the current and designing for the target first in a conceptual modeling level makes it easier and faster to see the change impact as well. It is also politically agnostic since conceptual data models use business language, and since e.g. technological aspirations are left out from the model it is easier to discuss and focus only on information topics that matters the most, e.g. ownership of data and other business process related data quality needs with the business stakeholders. Since conceptual model focuses only on business, business users and stakeholders do not need to feel uncomfortable of not understanding technological aspects of data management since there are no technological items visible.

For semantics and ontology creation, business driven conceptual model *is* the ontology for a business organization when agreed to be taken into use. Without having one, common language for communication and understanding can become a major obstacle, especially if common companywide efforts are created (like enterprise data warehousing or analytics combining more than one business subject areas together). Conceptual data models show and define concepts and their relationships between the concepts, which is one of the most important things in computer science and data management area as described in chapter 3.4.8. What comes to data governance, its role should be to keep the ontology maintained and also ensure it is consistently updated and approved to be used. Data governance explained in chapter 3.6.5 is not just about having data values and processes being managed consistently but it is also very much about keeping concepts and ontology up-to-date as well as including vocabularies and taxonomies. Different taxonomies like product or customer categorizations rely on the foundation of understandable, shared and approved ontology. If that is missing,

the guidance for implementation, shared knowledge and insight based on the knowledge is difficult. During the case study research work it became clear that in company X there is room for improvement to focus more on this level of information modeling, and making respective data governance built around the ontology in place. This would bring more efficiency in the overall knowledge sharing and insight creation as well.

4.1.2 Analysis of difficulties to agree semantics and ontology in practice

Several sources of theoretical framework have indicated how difficult it is to agree having common semantics in place companywide and agree on the definitions as a common ontology as described in chapter 3.4.8. Referring to a study made by Karel, Moore, Coit & Rose (2011), only 17% of organizations rated their current level of organizational maturity in relation to master data management as a "high" or "very high" classification in 2011 which was the same percentage of maturity in 2009. External study results represented by The Data Warehouse Institute (TDWI, www.tdwi.org) claim that 80% of business users are *not* capable of making their own queries and reports on the data kept in data warehouse because of the lack of understanding conceptually and logically what data is available and where it is in a data warehouse environment (Preibe, Reisser & Hoang 2011, 766). Although it is of course a question that how many business users do really need to make their own reports, the key thing still is that no matter who does the retrieval of data, it needs to be accessible, understandable, current and fit for the purpose of usage – meeting those data quality dimensions as necessary described in chapter 3.6.2.

It is not really a surprise that many companies are having difficulties managing the data and how to make it available consistently. The same have happened in company X. Therefore initiatives to improve the situation have been started of which this research is one kind of example. Still, the journey is just about to begin really, despite of having enterprise data warehouse technically in place for many years. As proposed in this research, the journey of improving business intelligence data quality should start with having semantics in place, at least the most important ones, and communicate and having an agreement to start to use it across the organization.

4.2 Data quality linkage to KPI structures and dimensional modeling

Looking on the strategic objectives of company X and their related key result and performance indicators, there is a clear need for business intelligence reporting and analytic solutions to support creation of holistic measurement across different business subject areas like marketing, sales and operational planning areas. This kind of progress is quite generalizable result of this research and which is common overall for many companies nowadays. There is also a clear demand for having product and customer related performance indicator metrics in place which would mean also that customer and product data quality should be evaluated against these business result and performance indicators.

When qualitative metrics are created for performance management to illustrate the trustworthiness of the indicator data, customer and product master data and related reference and business metadata becomes important and visible to business stakeholders. Getting more data is not necessarily the right future target but instead collecting less data but with a good enough quality with clearly defined purpose and meaning, and using statistical methods like stratified sampling method could be used as a main data gathering principle. Having semantically consistent business metadata and master data linkage to transactional data where it makes senses regarding the key business metrics and analytics would be the starting point for data quality improvements. This would drive for defining companywide business intelligence implementations using conformed dimensions around the facts in the whole enterprise.

As mentioned, data quality metrics needs to be linked to business KPI and KRI metrics in a way it reflects the essence of the actions they are created for. The problem is that what are key indicators and what are not is not clearly defined in company X. This creates also prioritization problem for data quality initiatives where to start data quality improvements. Nevertheless, this is an activity that needs to be planned and executed with the top management as discussed in theoretical framework chapter 3.2 since certain metrics are more important and higher in the hierarchy than others (the closer they

are to strategic targets and related critical success factors, the more important they are for the company).

From the data quality management perspective, information data quality linkage to key performance and result indicators are beneficial also in a sense it can drive the needed dimensional data quality (and thus focus on master and metadata needed to be in shape). These performance indicators with adjacent data quality indicators would be then analyzed by top management with the help of business analysts to define what the common business objectives are for the company. Depending on the level of how much uncertainty is required to be removed for the fact based business decision process, this would give also idea of needed data quality. As defined in the theoretical framework discussing about data quality in chapters 3.6.2 and 3.6.3, data needs to be in a quality level it meets the requirement to meet the expectation of the business, or as Cappiello, Francalaci and Pernici (2004, 68) defined it: fitness for use. Because the usage scenarios of the data can be various, the overall fitness for data quality needs to be agreed based on common data dimensions and ontology across the organization. This is naturally responsibility for business to define the level of fitness and not to be done IT organization by itself.

If the process described would be systematically applied and followed, in researcher's mind it would enable simple and efficient target setting process for IT organization unit to focus not only on technological matters but really put targets for IT to serve and provide needed analytical capabilities along with the operational targets to support daily business. It might also be beneficial way to close the gap between business and IT as interest groups inside a company also communication wise. With the common semantics using conceptual data models through logical and physical data modeling data management would also get the needed link to business goals, and the long lasting debate what is the business value of e.g. master data management, data warehousing etc. would gradually diminish. It would also bring the data management closer to business activities, and the evidence for having bad or good quality from the information perspective would become more visible outside of IT organization. This way business goals and data quality goals would not be any more two separate things but considered as one; this would also break the old-fashioned thinking that business goals are for the

business people, and data management goals are for IT people only since they should be a common joint effort and target.

4.3 Improving business intelligence data quality: organizational viewpoint

When motivation to start to improve the data quality areas starts to happen and increase its focus also for the business, there are lots of theoretical frameworks created how to go forward with data stewardship, data governance and other related data management principles and maturity assessment methods. The problem of these kind of generic frameworks are that there needs to be a business need to make them as initiatives to fly. Frameworks like The Open Group Architecture Framework (TOGAF), Control objectives for information and related technology (CoBIT) or Method for an Integrated Knowledge Environment (Mike 2.0) provide good starting point for organizations looking for frameworks and having no need to invent the wheel of governance models and topics by themselves. Frameworks provide guidelines for implementation but they do not do the work; that's what the organization needs to do by itself. Since time is scarce resource, it is important to start with a small quality improvement project that do not spend time and money too much but gives concrete benefit and hands-on example of improved things. These kinds of showing-by-example efforts can build business interests better than preaching of the frameworks itself to the top management. Framework is not the goal but a tool.

One of the most important organizational development areas for managing data quality is to arrange data governance as described in the theoretical framework chapter 3.6.5. Getting the commitment from the top business management level needs to be established. The semantic level improvement ideas illustrated in this case study should be managed in these kind of data governance organizational structures where the highest level of data governance should be steering group with representatives from different parts of a company, and which are operationally supported by nominated data stewards from the operational business units.

5 Thesis work results discussion

5.1 Conclusion of case study success criteria

In this case study, comprehensive work of creating theoretical framework as well as data gathering phase about the case of company X was conducted. The case and environment of the phenomenon was documented and described, and research study was connected to business intelligence development program where the findings were given as an input in an iterative way. Real life examples of data issues with real data was used in the analysis phase so the empirical observations was based on data that has been agreed and validated to represent real life cases and situation by different parties inside an organization.

Since the purpose of the descriptive case study was not to create new theories or compare the case with other cases outside the construct of this study, internal validity target was more about to cover widely enough the subject area. External validity in a way of using broad reference and literature materials was very thorough process, and getting different frameworks, studies, books and articles was investigated to bring a holistic theoretical framework to guide the study work. Regarding study reliability factors special efforts has been put to ensure that researcher's personal opinions didn't influenced in the outcomes of this research but was objectively analyzed based on the case study material.

Personal observations was done by participating in the activities of business intelligence data quality discussion and improvement projects to ensure reliability and objectiveness of the construct and analysis outcomes of it. From this viewpoint researcher's personal opinion is that the results of describing the case, related framework and information gathering as well as qualitative analysis are on a good solid base. The study content, illustrated cases and their analysis were also reviewed case by case with key practitioners during the research work project iteratively.

5.2 Personal evaluation of the value of research project

During the research and thesis report writing, research project brought value to business intelligence and master data management teams and projects. Research project was linked in the context of business intelligence development program for sales insight area but also even wider than that. During the exploration phase, communication of both theoretic framework and case study empirical findings was shared with colleagues and development program team members, and iterative discussions about the matters of data quality, semantics, ontology, data definitions and conceptual data modeling linkage to logical and physical data model implementations were discussed with other business functions as well.

This study has managed to bring the essence and reasoning of why semantics and having good enough data quality is required in business intelligence development area and how it can be improved from that perspective. These improvements being practical and small enough can solve real data quality issues. During the thesis work project it was also highlighted that the goal for data quality improvement is not to have 100% data quality in every place since it is impossible to reach such a goal and since it costs too much. Sometimes fit for purpose can be reached with lower data quality targets.

This case study and research work has increased also researcher's personal knowledge regarding the research subject area and that way managed to create new knowledge. This was one the targets and benefit to establish this research project. Research work and iterative collaboration during thesis work writing has enabled to clarify data quality problems in the subject area as well as proposing solutions for the identified problems. This study work have benefitted my personal goals to develop my skills and knowledge, and have served both the organizational and my personal targets by bringing new approach how to handle semantic data quality.

5.3 Further research topics to be considered

Considering the magnitude of the research subject area, further research might be needed especially on the ontological implementation side of enterprise data warehousing: how to keep track of consistent definitions, ontology and semantics in general

when multiple processes and systems are pushing data to enterprise data warehouse for analytical purposes. Another subject area to be investigated more could be based on social sciences and human behavior and how intrinsic and extrinsic motivators work in the area of quality management. Quality cannot be a separate matter in people's mind; you need to grow into it. In principle, when the importance of doing something having quality perspective in mind is clear and people understand their role in achieving together, people normally want to do their best - if they know why they need to do so. This could be another interesting area to investigate and compare how big part these kind of intrinsic motivators play in the quality management compared to extrinsic motivators like monetary incentives.

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6 Attachments

6.1 Attachment 1: Theoretical framework as RDF/OWL presentation

```
<?xml version="1.0"?>


<!DOCTYPE rdf:RDF [
    <!ENTITY owl "http://www.w3.org/2002/07/owl#" >
    <!ENTITY xsd "http://www.w3.org/2001/XMLSchema#" >
    <!ENTITY rdfs "http://www.w3.org/2000/01/rdf-schema#" >
    <!ENTITY rdf "http://www.w3.org/1999/02/22-rdf-syntax-ns#" >
]>


<rdf:RDF xmlns="http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#"
     xml:base="http://www.haaga-helia.fi/ONT_Ari_Anturaniemi"
     xmlns:rdfs="http://www.w3.org/2000/01/rdf-schema#"
     xmlns:owl="http://www.w3.org/2002/07/owl#"
     xmlns:xsd="http://www.w3.org/2001/XMLSchema#"
     xmlns:rdf="http://www.w3.org/1999/02/22-rdf-syntax-ns#">
    <owl:Ontology rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi"/>



    <!--

///////////////////////////////////////////////////////////////////////
////////////////////
    //
    // Object Properties
    //

///////////////////////////////////////////////////////////////////////
////////////////////
     -->




    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#affect_to -
->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#affect_to"/>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#creates -->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#creates"/>
```

```
    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#defines -->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#defines">
        <rdfs:subPropertyOf
rdf:resource="&owl;topObjectProperty"/>
    </owl:ObjectProperty>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#executes --
>

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#executes"/>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#explains --
>

    <owl:ObjectProperty rdf:about="http://www.haaga-
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    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#follows_up
-->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#follows_up"/>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#has -->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#has"/>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#is_a -->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_a">
        <rdfs:subPropertyOf
rdf:resource="&owl;topObjectProperty"/>
    </owl:ObjectProperty>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_compared_to -->
```

```
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helia.fi/ONT_Ari_Anturaniemi#is_compared_to"/>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#is_created
-->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_created"/>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_created_from -->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_created_from"/>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_defined_against -->

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helia.fi/ONT_Ari_Anturaniemi#is_managed_by -->

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_managed_by"/>
```

```
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-->

    <owl:ObjectProperty rdf:about="http://www.haaga-
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    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_modeled_as -->

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helia.fi/ONT_Ari_Anturaniemi#is_modeled_as"/>



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helia.fi/ONT_Ari_Anturaniemi#is_planned_as -->

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    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_related_to -->

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    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#is_shared -
->

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    <owl:ObjectProperty rdf:about="http://www.haaga-
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    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#measures --
>

    <owl:ObjectProperty rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#measures"/>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#sets -->
```

```
    <owl:ObjectProperty rdf:about="http://www.haaga-
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    <owl:ObjectProperty rdf:about="http://www.haaga-
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    <!--

///////////////////////////////////////////////////////////////////
////////////////////
    //
    // Classes
    //

///////////////////////////////////////////////////////////////////
////////////////////
     -->



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Action -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Action">
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helia.fi/ONT_Ari_Anturaniemi#Operations"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#affect_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_result"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_organization -->

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helia.fi/ONT_Ari_Anturaniemi#Business_organization">
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            <owl:Restriction>
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helia.fi/ONT_Ari_Anturaniemi#has"/>
```

```
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rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Quality"/>
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        </rdfs:subClassOf>
        <rdfs:subClassOf>
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                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#has"/>
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rdf:resource="http://www.haaga-
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            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-
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        <rdfs:subClassOf>
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rdf:resource="http://www.haaga-
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    <!-- http://www.haaga-
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        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_organization"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_compared_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_result"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
```

```
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#uses"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Insight"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_measured"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_measurement"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#uses"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Knowledge"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_managed_by"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Management"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Conceptual
-->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Conceptual">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Model"/>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Contextual
-->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Contextual">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data_quality_target"/>
    </owl:Class>
```

```
    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Data -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data">
        <rdfs:subClassOf rdf:resource="&owl;Thing"/>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data_quality_target -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data_quality_target">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Quality"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_related_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Decision --
>

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Decision">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Management"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#affect_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Operations"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#uses"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Insight"/>
            </owl:Restriction>
        </rdfs:subClassOf>
```

```
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#uses"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_measurement"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Dimensional
-->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Dimensional">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Model"/>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Executed_action -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Executed_action">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Action"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_related_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Present"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_related_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Past"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Future -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Future">
```

```
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_result"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_estimated"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lead_indicator"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Information
-->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Information">
        <rdfs:subClassOf rdf:resource="&owl;Thing"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_modeled_as"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Conceptual"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#creates"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Knowledge"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#defines"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Insight -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Insight">
        <rdfs:subClassOf rdf:resource="&owl;Thing"/>
```

```
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_created_from"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Knowledge"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Intrinsic -
->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Intrinsic">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data_quality_target"/>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Key_performance_indicator -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Key_performance_indicator">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_indicator"/>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Key_result_indicator -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Key_result_indicator">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Result_indicator"/>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Knowledge -
->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Knowledge">
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#uses"/>
```

```
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Information"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lag_Indicator -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lag_Indicator">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_measurement"/>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lead_indicator -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lead_indicator">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_measurement"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#explains"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lag_Indicator"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Logical -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Logical">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Model"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#defines"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>
```

```
    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Management
-->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Management">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_organization"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#sets"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_target"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Master_data
-->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Master_data">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data"/>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Metadata --
>

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Metadata">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data"/>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Model -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Model"/>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Operations
-->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Operations">
```

```
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_organization"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#has"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data_quality_target"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#executes"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_target"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Past -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Past">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_result"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#affect_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lag_Indicator"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_indicator -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_indicator">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lead_indicator"/>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_measurement -->
```

```
    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Performance_measurement">
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#measures"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_result"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#has"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data_quality_target"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#creates"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Knowledge"/>
            </owl:Restriction>
        </rdfs:subClassOf>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#uses"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Physical --
>

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Physical">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Model"/>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Planned_action -->
```

```
    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Planned_action">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Action"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_related_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Future"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Present -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Present">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_result"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#affect_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lag_Indicator"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Quality -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Quality">
        <rdfs:subClassOf rdf:resource="&owl;Thing"/>
        <rdfs:subClassOf>
            <owl:Restriction>
                <owl:onProperty rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#is_related_to"/>
                <owl:someValuesFrom
rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Business_target"/>
            </owl:Restriction>
        </rdfs:subClassOf>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Result_indicator -->
```

```
    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Result_indicator">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lag_Indicator"/>
    </owl:Class>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Transactional_data -->

    <owl:Class rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Transactional_data">
        <rdfs:subClassOf rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Data"/>
    </owl:Class>



    <!--

///////////////////////////////////////////////////////////////////
////////////////////
    //
    // Individuals
    //

///////////////////////////////////////////////////////////////////
////////////////////
     -->




    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Accuracy --
>

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Accuracy">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Intrinsic"/>
    </owl:NamedIndividual>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Completeness -->

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Completeness">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Contextual"/>
    </owl:NamedIndividual>
```

```
    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Consistency
-->

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Consistency">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Contextual"/>
    </owl:NamedIndividual>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Currency --
>

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Currency">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Contextual"/>
    </owl:NamedIndividual>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Identifiability -->

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Identifiability">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Contextual"/>
    </owl:NamedIndividual>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Lineage -->

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Lineage">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Intrinsic"/>
    </owl:NamedIndividual>



    <!-- http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Reasonabless -->

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Reasonabless">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Contextual"/>
    </owl:NamedIndividual>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Semantic --
>
```

```
    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Semantic">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Intrinsic"/>
    </owl:NamedIndividual>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Structure -
->

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Structure">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Intrinsic"/>
    </owl:NamedIndividual>



    <!-- http://www.haaga-helia.fi/ONT_Ari_Anturaniemi#Timeliness
-->

    <owl:NamedIndividual rdf:about="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Timeliness">
        <rdf:type rdf:resource="http://www.haaga-
helia.fi/ONT_Ari_Anturaniemi#Contextual"/>
    </owl:NamedIndividual>
</rdf:RDF>



<!-- Generated by the OWL API (version 3.2.3.1824)
http://owlapi.sourceforge.net -->
```

6.2 Attachment 2: Data modeling methodology notation comparison by Scott Ambler (Ambler 2006)

Notation	Information Engineering	Barker Notation	IDEF1X	UML
Multiplicities:				
- Zero or one			Z	0..1
- One only			1	1
- Zero or more				0..*
- One or more			P	1..*
- Specific range	N/A	N/A	N/A	3..7
Attributes:				
Names	N/A	Attribute Name: Type	attribute-name: Type	attributeName: Type
Primary key/unique identifier	N/A	# Attribute Name	attribute-name	attributeName <<PK>> {order=#}
Foreign key	N/A	N/A	attribute-name (FK)	attributeName <<FK>> {to=tablename}
Associations:				
Labels	Cust-omer owns accessed by Account	Cust-omer owns accessed by Account	Customer owns accessed by Account	Cust-omer owns Account
Entity roles	N/A	N/A	N/A	Cust-omer owner
Subtyping	Sub Type is a Super Type	Super Type Sub Type	Sub Type attr Super Type	Sub Type Super Type
Aggregation	Part is part of Whole	Part part of Whole	Part is part of Whole	Part Whole
Composition	Part is part of Whole	Part part of Whole	Part is part of Whole	Part Whole
Or Constraint	Person Customer Employee	N/A	N/A	Person {or} Customer Employee
Exclusive Or (XOR) Constraint	Item Product Service	Item Product Service	N/A	Item {xor} Product Service

6.3 Attachment 3 (confidential): Empirical part of case study

see separate file.