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Business Intelligence and Developing Management Reporting

Action research in a case organization

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TIIVISTELMÄ:

Business Intelligence (BI) eli liiketoimintatiedon hallinta on prosessi, joka viittaa kaikkeen olennaiseen tietoon, jota organisaatiot järjestelmällisesti keräävät ja analysoivat päätöksenteon parantamiseksi. Liiketoimintatiedon hallinnan tavoitteena on kerätä, analysoida, käsitellä, tallentaa ja toimittaa reaaliaikaista tietoa organisaation tarpeisiin sekä sen tehokkuuden seurantaan. Uudet teknologiat mahdollistavat rajattoman tiedonkeruun, ja datasta onkin tullut organisaatioiden kilpailuvaltti. Tämä on aiheuttanut kuitenkin sen, että organisaatioilla on haasteita tunnistaa, mikä data on olennaista heidän liiketoiminnalleen, ja erityisesti, että kuinka prosessoida tieto hyödylliseksi informaatioksi ja päätöksenteon tueksi. Tietoa tarvitaan tehokkaaseen päätöksentekoon, ja ajantasainen tieto luo organisaatiolle enemmän arvoa ja uusia mahdollisuuksia. Erilaisilla BI-työkaluilla eri lähteistä kerätty tieto voidaan integroida ja muuntaa luettaviksi reaaliaikaisiksi raporteiksi, mikä tukee johdon päätöksentekoprosessia.

Tässä toimintatutkimuksessa selvitettiin, miten tehokkaan liiketoimintatiedon avulla voidaan automatisoida ja digitalisoida johdon raportointia esimerkkiorganisaatiossa. Tutkimus toteutettiin maailmanlaajuiseen teknologiayritykseen ja pilotoitiin sen yhteen liiketoimintalinjaan. Tutkimuksen tarkoituksena oli löytää ratkaisuja organisaation jatkuvan parantamisen ja laatukustannusdatan integrointiin johdon raportoinnin näkökulmasta sekä edistää muutosta organisaation sisällä. Tutkimus oli rajoitettu koskemaan vain esimerkkiorganisaation sisäistä liiketoimintatietoa.

Tutkimuksen aikana luotiin käyttäjäystävällinen, näkyvä ja online-tietoon perustuva raportointijärjestelmä. Automatisoitu ja digitalisoitu prosessi hyödyntää BI-työkalua, Microsoft Power BI:ta, ja mahdollistaa prosessoitujen laatukustannustietojen saamisen ulos yhdestä kanavasta. Tutkimus osoitti, että vaikka käytössä olisikin edistyksellisiä ja tehokkaita BI-työkaluja, se ei poista datan laadun merkitystä. Jopa kaikkein tehokkaimmat raportointityökalut ovat turhia, jos niiden hyödyntämä tieto ei ole korkealaatuista. Tämän tutkimuksen mukaan huonolaatuinen data ei tuota vain epäluotettavia raportteja, vaan on myös merkittävä este tietojen integroinnille. Jos data on eri muodoissa useissa eri järjestelmissä, sitä on mahdotonta integroida. Jotta datan laatu voidaan taata ja tietoa voidaan hyödyntää tehokkaasti organisaation tarpeisiin, on dataa säännöllisesti ylläpidettävä ja puhdistettava. Datan laatu on ensisijaisesti liiketoimintakysymys. Tämän tutkimuksen mukaan datan visualisointi voi olla arvokas työkalu laadunvalvonnassa, koska se paljastaa ongelmat tiedossa ja tiedonkeruussa välittömästi, samoin kuin myös virheet IT-järjestelmässä.

AVAINSANAT: Business Intelligence; Management reporting; Data quality; Data integration; Action research;

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ABSTRACT:

Business Intelligence (BI) is a process, which refers all the essential information, which organizations systematically gathers and analyse to aid more accurate decision-making. Target of the Business Intelligence is to collect, analyze, process, store and deliver the real-time information for an organization´s needs, as well as, follow the effectiveness. New technologies enable limitless data collection and data has become valuable asset for organizations. However, another problem occurred as organizations have challenges to identify, which data is relevant for their business and operations, and more importantly, how to process the data to useful information and a source of effective decision making. Data is needed for efficient decision making and up-to-date data brings more value and new opportunities for the organization. With BI tools, data can be integrated and transformed to readable reports, which supports management decision making process.

In this action research we were studying how the management reporting can be automatized and digitalized with efficient Business Intelligence in a case organization. With this research we were trying to find solutions for a case organization´s problematic practices and processes in continuous improvement (CI) and cost of poor quality (COPQ) data integration from a management reporting perspective and promoting change within the organization. The research was limited to concern only with the case organization´s internal Business Intelligence and internal data.

During the research, a user friendly, visible and on-line data-based reporting procedure was created. The generated automatized and digitalized process benefits the BI tool, Microsoft Power BI, and enables one to retrieve processed COPQ information out from one channel. The research showed that even though there are progressive and effective BI tools in use, it does not remove the meaning of data quality. Even the most powerful reporting tools are useless, if the data is not high-quality and clean. According to this research, bad data is not just producing unreliable reports, but it is also obstacle for data integration. If the data is in various formats in several systems, it is impossible to integrate. To be able guarantee the data quality and to be able to exploit the data effectively, it requires maintaining and cleaning the data regularly. Data quality is primarily a business issue. According to this study, data visualization can be a valuable tool in quality control as it reveals errors in data and data collection immediately, as well as, errors in the IT-system.

KEYWORDS: Business Intelligence; Management reporting; Data quality; Data integration; Action research;

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Abbreviations

API	Application Programming Interface
BI	Business Intelligence
CDC	Change Data Capture
CI	Continuous Improvement
COPQ	Cost of Poor Quality
CRM	Customer Relationship Management
DDDM	Data-Driven Decision Making
DSS	Decision Support Systems
ERP	Enterprise Resource Planning
ELT	Extract-Load- Transform
ETL	Extract-Transform-Load
IA	Immediate Actions
IT	Information Technology
KDD	Knowledge Discovery in Data
KPI	Key Performance Indicator
MTD	Month to Date
OLAP	Online Analytical Processing
SCM	Supply Chain Management
YTD	Year to Date

1 Introduction

Digitalization has been a driver for many organizations to renew their processes and ways of working. New business models occur, and new digital tools are designed to improve the performance of organisations. Although there is no digitalization without data, it has become a base for digitalization and in addition, there is more data available than ever before. New technologies enable limitless data collection and data has become valuable asset for organizations. However, another problem has occurred as organizations experience challenges to identify, which data is relevant for their business and operations, and more importantly, how to process the data into useful information and source of effective decision making.

Business Intelligence (BI) is a process, that refers all the essential information, which organizations systematically gather and analyze to aid accurate decision-making. The target of the Business Intelligence is to collect, analyze, process, store and deliver real-time information for the needs of organizations, as well as follow the effectiveness. Business Intelligence includes internal data, which comes from company sources, as well as external data, which derives from the market where the company operates. With BI tools, data can be integrated and transformed into readable reports, which supports the management decision making process.

In this research we are studying how management reporting can be automatized and digitalized with efficient Business Intelligence in a case organization. The case organization has a need to renew their processes and ways of working, partly because of digitalization. With this research we are trying to find solutions for the problematic processes of the case organisation in continuous improvement (CI) and cost of poor quality (COPQ) data integration from management reporting perspective and promoting change within the organization. This development project derives from the business transformation project of the case organization, which is aiming to bring people, process and technology to closer to its business strategy and vision.

The research is conducted as an action research, which is a process aiming the transformative change through the simultaneous process of acting and carrying out research. As data and data management are crucial elements of Business Intelligence, the literature review focuses to clarify those terms and their relations, as well as, highlights the role of data quality in efficient decision making. In the figure 1 the research process is shown.

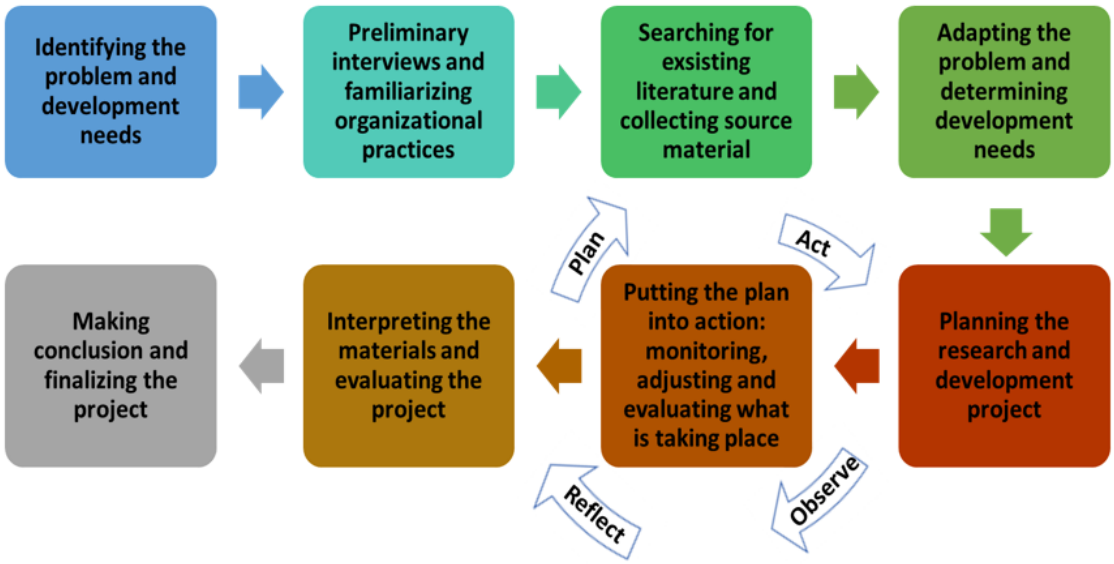

Figure 1. Research process.

The research is limited to concern only the internal Business Intelligence of the case organization and specifically developing continuous improvement and cost of poor-quality data integration and reporting. Therefore, this study is limited only to the internal data of the organization. External data, which includes information on competitors and markets of the organization (Nykänen et. al., 2016), is not in the scope of this study.

1.1 Problem Setting and Research Questions

In the case organization management reporting is time consuming and it causes lots of manual work. However, the target of management reporting is to provide relevant,

reliable and up to date information about the financial situation of organization and to support target setting, as well as adhering to the strategy. For effective decision making it is relevant to receive online data of organizational performance.

Business Intelligence solutions enables efficient and automatized reporting. On-line data can be collected from several data management systems and then all the essential information is shown in one BI solution. Available on-line data enables changes to be noticed quickly, and corrective actions can be performed immediately. It makes organizational decision making effective and helps to maintain focus. From this perspective we are studying how the management reporting of the case organization can be automatized and digitalized with efficient Business Intelligence. In this research we are focusing on improving the continuous improvement of the case organization and the cost of poor-quality data reporting practices.

The main objective of this research is outlined in the following research question (RQ):
RQ1: How organizational reporting can be developed to guarantee efficient Business Intelligence?

- How to automatize handling and visualization of data from different systems to help improvement and analytics?

Furthermore, this research aims to provide some insights on how Business Intelligence and efficient data management can improve effective management and on-time decision-making.

1.2 Research Approach

The research is conducted as a multi-method qualitative study. It is carried out in a case organization, which is a global developer and supplier of lifecycle solutions based on high-quality products, processes and services. Before initiating the research project, the case organization was observed, and preliminary interviews were conducted to identify some of the key challenges of management reporting and data management. However,

the preliminary interviews and observations reveled challenges and the need of improvement in the practice of the case organization, for example (1) to have a more user friendly, reliable, visible and on-line data based way of working – automated and digitalized as far as possible, (2) to get all the needed processed cost of poor quality information out from one channel without manual work, (3) to build better integration between enterprise resource planning (ERP) data and continuous improvement data to provide reliable reporting of COPQ with proper problem area and root cause coding and (4) need for better standardized practices. These preliminary observations guided empirical research design.

2 Data Management

Data and data management are crucial elements of Business Intelligence. Data management supports the defining of strategy, management and use of business data in organizations. Operationally it also supports development and maintenance of information systems. (Gordon, 2013, p. 60) Digitalization and rapid development of new technologies has enabled more data to be available than ever before and the volume is constantly increasing (Drăgan & Metz, 2017). Organizations are struggling with the information flow and they are trying to identify which information is relevant for their business. Data is an asset for the organizations, although its value does not increase through storage (Markkula & Syväniemi, 2015, p. 72). Data must be processed into information and knowledge until it is beneficial. Data management contains all the disciplines related to managing data as a valuable resource. It is the development, execution and supervision of plans, policies, programs and practices that control, protect, deliver and increase the value of data and information assets. (Lawrence, 2009, p. viii)

2.1 From Data to Wisdom

One of the most important value chains in organizations goes through from data to information and knowledge to understanding (Markkula & Syväniemi, 2015, p. 21). To be able to understand Business Intelligence it is essential to determine relations between these terms and their hierarchy from a knowledge management perspective. Their relation is usually described as a pyramid ascending from data to wisdom (Anand & Singh, 2011) as shown in figure 2. Data is needed to create information, which is essential to gain knowledge and wisdom. However, the amount of data is not relevant but the capability of the organization to adapt it in practice. Data is raw, random, and unorganized (Sherman, 2014. p. 8) and it must be organized, structured, and processed to information until it supports organizational decision-making (Markkula & Syväniemi, 2015, p. 21, 37). However, information is what we use to gain knowledge and when we process it in a meaningful way, it turns into wisdom (Sherman, 2014. p. 8-9).

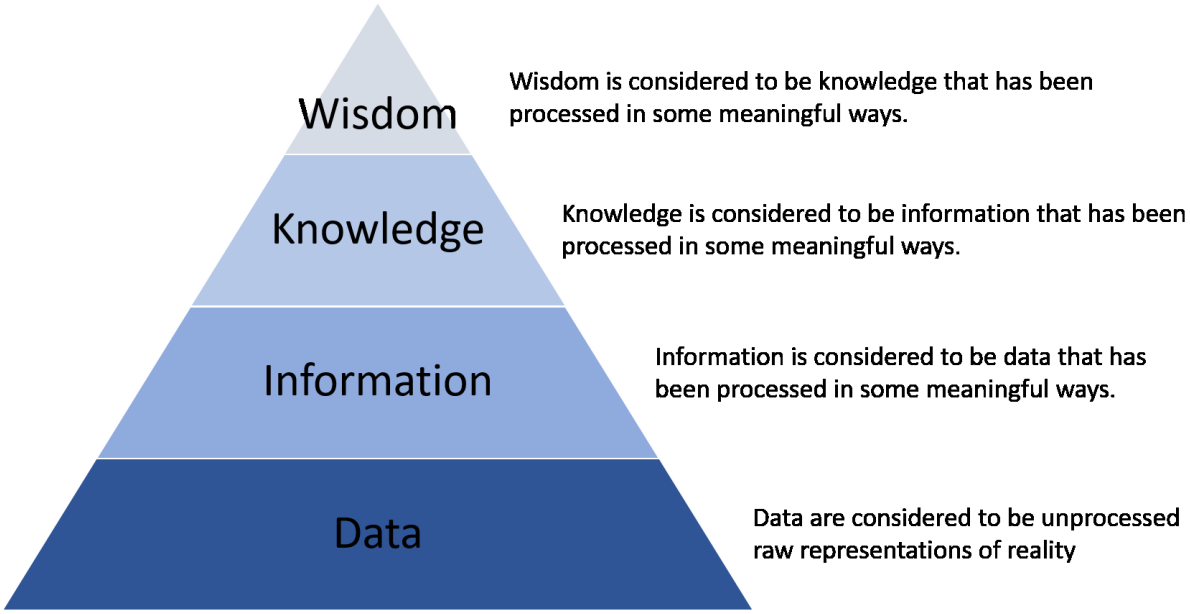

Figure 2. Knowledge pyramid (Modified from Anand & Singh, 2011)

Intelligence can be seen somewhere between knowledge and wisdom. It is ability to acquire, perceive and understand information, and to retain it as knowledge (Harlon, 2016). It is associated with learning as it can be gained by searching information and knowing more. This way it can be seen as a next stage of knowledge. Therefore, the final stage is wisdom (Harlon, 2016), which is the Intelligence that we gain in the process of learning from the mistakes that we do (Andrew, 2010).

2.2 Categorizing data

Data can be categorised several different ways. The sources of data can be divided to external and internal categories. External data is sourced outside of organization and it includes information on competitors and markets of the organization. Internal data relates the data inside the organization, like sales, finance, marketing and human resources. (Nykänen et. al., 2016)

Data can be divided to quantitative and qualitative data. Quantitative data is about numeric variables, which can be counted, measured and expressed as numbers. Qualitative data is about categorical variables, which can be categorized based on traits and characteristics. It can be presented by a name, symbol or code. (Australian Bureau of Statistics, 2013)

Data can be divided into four categories as shown in figure 3:

- unstructured data, for example documents, video, audio, etc.
- semi-structured data, for example software packages/modules, spreadsheets, and financial reports
- quasi-structured data, for example data about webpages a user visited and in what order
- structured data. (Cai & Zhu, 2015; Nykänen et. al., 2016; Ommi, 2020)

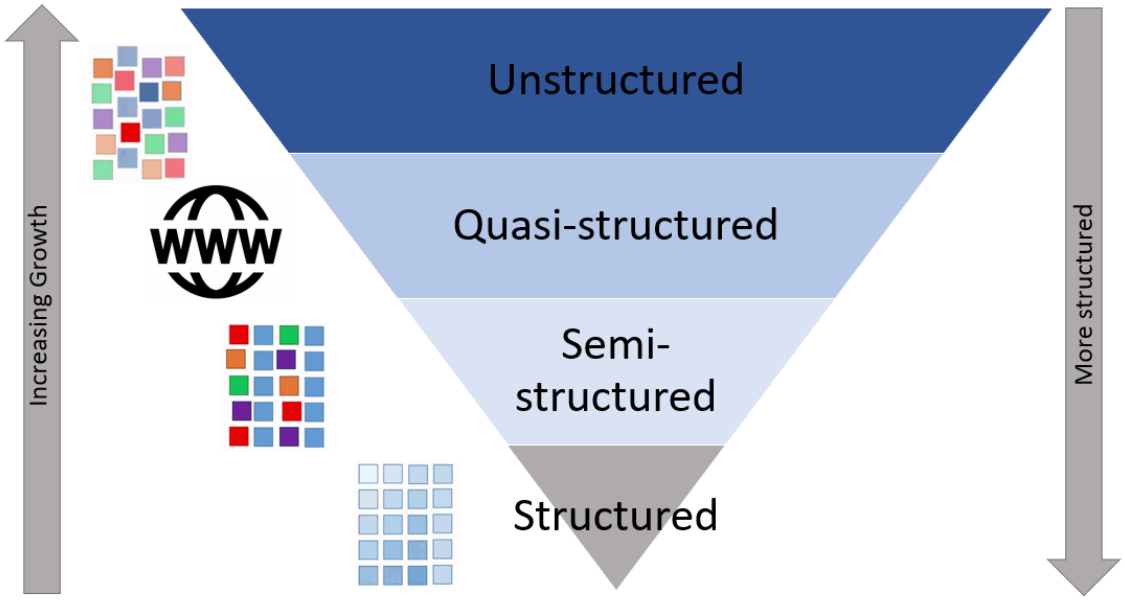

Figure 3: Four categories of data (Modified from Ommi, 2020)

Structured data refers to any data in specific format having a defined data model. It is easy to store in rows and columns of relational databases. It is the data, which organizations can get easily out of their databases and business applications. Quantitative data

is almost always considered structured data. Semi-structured data has clear self-describing patterns and structure, but it does not have a standard data model. Quasi-structured data instead, consists of textual content with erratic data formats. It is formatted with effort, software system tools, and time. Unstructured data, on the other hand, refers to the data in many different formats and it does not follow the conventional data models. (Ommi, 2020) One of the most common types of unstructured data is text, which can be generated and collected in a wide range of forms, for example e-mails, Word-documents and survey responses (Rouse, 2018). Qualitative data is almost always considered unstructured data or semi-structured data.

Automatized handling of structured data has been managed for a long time, unlike handling of unstructured data. Traditionally, it contains lots of manual work. The challenge of data management is that more than 80 % of the total amount of data in existence is unstructured data (Cai & Zhu, 2015). However, recent development of big data platforms and analytics techniques has enabled automatized handling of unstructured data and its utilization for Business Intelligence and analytics applications (Rouse, 2018). Therefore, organizations can benefit the unstructured data more efficiently than earlier.

One of the most important elements for big data analysis and solutions is metadata. From a technical point of view, it is not a separate data structure as it provides additional information about a specific set of data. It is a data about data as it provides information about other data. (Big Data Framework, 2020)

2.3 Collecting Data

Collected data is not automatically valuable and it is not always brining competitive advantage. If the collecting of data is concentrating quantity instead of quality and usability, it may cause information flow that exceeds the capacity and disables the business processes. (Laihonen et. al., 2013, p. 44) Organizations must define which data is relevant, and which is needed to collect to support their strategic decisions and gain their strategic goals.

There are multiply ways of collecting organizational data. In organizations it is quite usual that all the required data is available, but it has been spread to several sources, for example in ERP-systems and databases. Data may also be in multiple formats that causes challenges. On the other hand, managing raw data in databases is relatively easy and it can be moved from one place to another without losing the content. However, transferring the information from one people to another, via information systems, is much more challenging (Kaario & Peltola, 2008, p. 6).

2.4 Data Integration

To be able to benefit and analyze the collected data, it often requires that data must be integrated. Data integration means combining data from different sources and bringing it together to ultimately provide a unified view (Sherman, 2014. p. 14). These activities are usually the most time and resource-consuming portion of building Business Intelligence environment. (Sherman, 2014. p. 301).

Earlier days data integration required lots on manual work, but nowadays there are several different methods for automated data integration. The most common data integration method is Extract, Transform and Load (ETL) -process. It copies the data from different systems and collects them together to harmonize and load into a database or a data warehouse. (Rouse, 2019) According to Rouse (2019) the other major data integration methods for different types of uses are:

- Extract, load and transform (ELT): Data is loaded into a data system and transformed later for specific analytics uses
- Change data capture (CDC): Changes of data are identified in databases and applied to a data warehouse or other repository
- Data replication: The data in a database is replicated to others to keep the information synchronized
- Data virtualization: Data from different systems is combined virtually to create a unified view for end users

- Streaming data integrations: integrating data sources in real-time to provide up-to-the-minute information.

2.5 Data Quality

Poor quality data runs the risk of bad analysis and completely wrong predictions (Drăgan & Metz, 2017). It may have serious consequences in organizational decision-making. Through digitalization, more and more systems are integrated with each other and organizational data is collected and analyzed from multiple sources. The poor-quality data in one system can affect negatively to the function of another system causing serious, unpleasant consequences for the organization. Poor data quality has also a negative impact on operational costs as detecting and correcting errors takes time and resources (Drăgan & Metz, 2017).

Bad data quality may be obstacle for data integration. The receiving information system may not interpret the data, or it interprets the received data the wrong way so that the original meaning changes (Gordon, 2013, p. 8). Generating poor data into a required format may be so difficult that integration is not even cost-efficient. (Kaario & Peltola, 2008, p. 64) That is why data quality and authenticity must always be ensured, before storing the data (Markkula & Syväniemi, 2015, p. 49, 56-57).

There are number of reasons that cause poor data quality. Some of them are technical and some human error. Gordon (2013, p. 92) have listed the causes of poor data quality:

- Inappropriate schemas in databases
- Errors done, when entering the data
- Data has been outdated over time
- Data has been corrupted when moved between systems
- Lack of understanding when using the data.

In organizations the requirement for information is constantly changing. If the data is poor or it is ambiguously defined, it may be difficult to respond to the new information requests. (Gordon, 2013, p. 8). Therefore, to be able guarantee the data quality and to be able to exploit the data effectively, it requires maintaining and cleaning the data regularly. As organizations are producing huge amount of data daily, it requires lots of work. This is why organizations concentrate usually only on critical data (master data) of organization and its quality, instead of transaction data. However, sometimes analyzing transaction data might bring new insights to the organization. (Laihonen et. al., 2013, p. 19-20)

When evaluating data quality, we should consider five quality dimensions presented in table 1: availability, usability, reliability, relevance and presentation quality (Cai & Zhu, 2015). However, according to Drăgan & Metz (2017) the most important data quality elements, that should be considered for business purposes, are accessibility, credibility, accuracy, consistency, completeness, integrity and readability.

Quality dimension	**Quality elements**
Availability	Timeliness
	Accessibility
Usability	**Credibility**
	Accuracy
Reliability	**Consistency**
	Integrity
	Completeness
Relevance	Fitness
Presentation quality	**Readability**

Table 1. Data quality elements and important data quality elements for business purposes (Cai & Zhu, 2015; Drăgan & Metz, 2017)

Before the BI tools can deliver actionable information to organizational needs, the quality of the data must be ensured. The data must be clean, consistent, conformed, current, and comprehensive, but it cannot be produced without strategy to manage the information (Sherman, 2014, p. 10, 12).

2.6 Visualizing Data

Data presentation is an essential part of the BI process. It describes the interfacing layer between data and humans, where data is presented to the users in chosen forms and formats. Data visualization, however, is a graphical or visual method of presenting data. (Zheng, 2017) Data visualization presents information pictorially, often graphically, helping communicate it in a more intuitive way (Sherman, 2014. p. 401). According to Padghan (2019) the data visualization lies at the intersection of design, communication and information science, as shown in the figure 4.

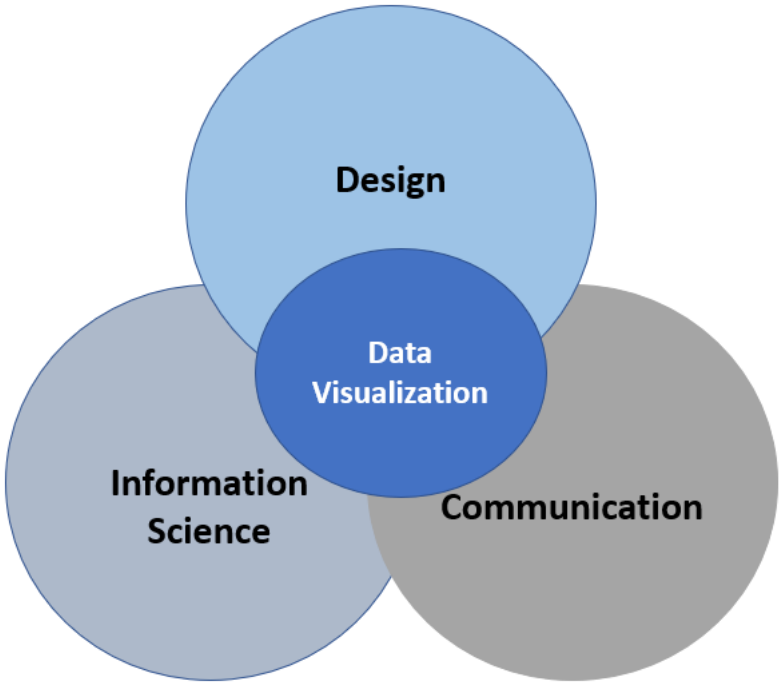

Figure 4: Data Visualization (Modified from Padghan, 2019)

Data visualization has remarkable role in Business Intelligence as it enables large volumes of information to be rapidly interpreted and comprehend. With BI tools, data is easy to transform into visuals and study from different perspectives. It also enables the detection of problems as they become immediately apparent. Therefore, data visualization reveals errors in data itself, as well as, data collection. This way visualization can be

a valuable tool in quality control. (Ware, 2013, p. 3-4) Good visualization allows for the drilling in and finding of more data about anything that seems important. (Ware, 2013, p. 317)

3 Business Intelligence

Richard Devens used the term “Business Intelligence” in his book *“Cyclopaedia of Commercial and Business Anecdotes”* already in 1865 to describe how a financier had successfully beaten his competitors by understanding the market and surrounding conditions better than they did (Lebied, 2017; Balakrishnan & Raul 2018). In 1958 IBM employee Hans Peter Luhn used the term Business Intelligence and defined intelligence as *“the ability to apprehend the interrelationships of presented facts in such a way as to guide action towards a desired goal.*" (Cebotarean, 2011; Balakrishnan et. al., 2018). However, the Business Intelligence term in Modern sense was not widespread until 1990´s (Nedelcu, 2013; Cebotarean, 2011).

Over the years, the process of Business Intelligence has been developed to solve the challenges while dealing with data by involving newer tools and techniques. According to Padghan (2019) there can be seen three development phases in the history of Business Intelligence:

1. Technical (IT to End User)
2. Self-Service (Analyst to End User)
3. Everyone (End User)

In the first phase, end users were fully depending on IT department for data insights as they did not have possibility to create visualizations or reports on their own as the tools required technical knowledge. The Self-Service phase enabled people with some knowledge of analytics to use BI tools. This second phase gave better access to data and with the help of analysists more people could have better data insights. In the third phase anyone who had basic understanding of the data could create visualizations or reports and share them with others. (Padghan, 2019) Therefore, data and Business Intelligence had become privilege of everybody.

3.1 The Definition of Business Intelligence

Business Intelligence is a process, which refers to all the essential information which organizations systematically gather and analyze to aid accurate decision-making. Massive amounts of raw data are collected from various resources and transformed into useful information and knowledge, which enables organizations to make better data-driven business decisions and meet the strategic needs of the company (Obeidat, Richardson, Rattanak & North, 2015; Riahi, 2018). Business Intelligence presents data to business people so that they can use it to gain knowledge (Sherman, 2014. p. 14). According to Gordon (2013, p. 141)

> *Business intelligence is the name that has been given to the set of "techniques" that is used to transform raw data into information that can be used to inform high-level decision making.*

Sauter (2014, p. 57), on the other hand, defines Business Intelligence as a change in how people do business and how this change is built upon having information, processes and tools needed to make decisions. According to Khan and Qaudri (2012) the objective of Business Intelligence is to improve the timeliness and quality of information. For managers it enables better understanding where their company is positioned compared to competitors (Khan & Qaudri, 2012). In existing literature Business Intelligence, there are several different terms and definitions depending on region and author: competitive intelligence, competitor intelligence, market intelligence etc. (Vuori, 2006).

Business Intelligence alone is not driving organization to success. It brings value only, when it is properly managed. Business Intelligence exists in every organization, even they are not aware of it and they do not have specific procedures for this. However, every organization is collecting and storing some data and carrying out decisions and action plans based on the information. When these procedures are carried out systematically in interaction with other, it creates a Business Intelligence process. (Laihonen et. al., 2013, p. 46). Typically, the BI process consists of data management, data analysis and data presentation (Zheng, 2017). In the figure 5 the BI process is described with the crucial

tasks. To be able to guarantee efficient Business Intelligence it must be well organized and responsible persons must be defined. (Laihonen et. al., 2013, p. 46).

Figure 5: Business intelligence process and crucial tasks. (Modified from Laihonen et. al., 2013, p. 46)

When the Business Intelligence is properly managed, it will benefit the organization many ways. Benefits of Business Intelligence is shown in the figure 6. Business Intelligence allows a quick response to business queries and enables the real time analysis with quick navigation. It allows faster and more accurate reporting, analyzing and planning. It also helps to identify several cross functional opportunities, as well as reduces the risk of bottlenecks. It helps to improve data quality and operational efficiency, as well as customer and employee satisfaction. Nevertheless, it helps to know the business better, improves decision making and increases competitive advantage. It also helps to allocate the resources and reduce the costs. (Padghan, 2019; BI-survey.com, 2020)

Figure 6: Benefits of Business Intelligence (Modified from Padghan, 2019; BI-survey.com, 2020)

3.2 BI Architecture

Business Intelligence architecture is a frame for organizing the data, information management and technology components that are used to build Business Intelligence systems for reporting and analyzing the data (Rouse, 2010). A typical structure of BI architecture consists of the following elements:

- Data sources
- Data integration
- Data Warehouse
- Analyzing, Data Mining and Online Analytical Processing (OLAP) and reporting tools
- Front-end applications (Chaudhuri et. al., 2011)

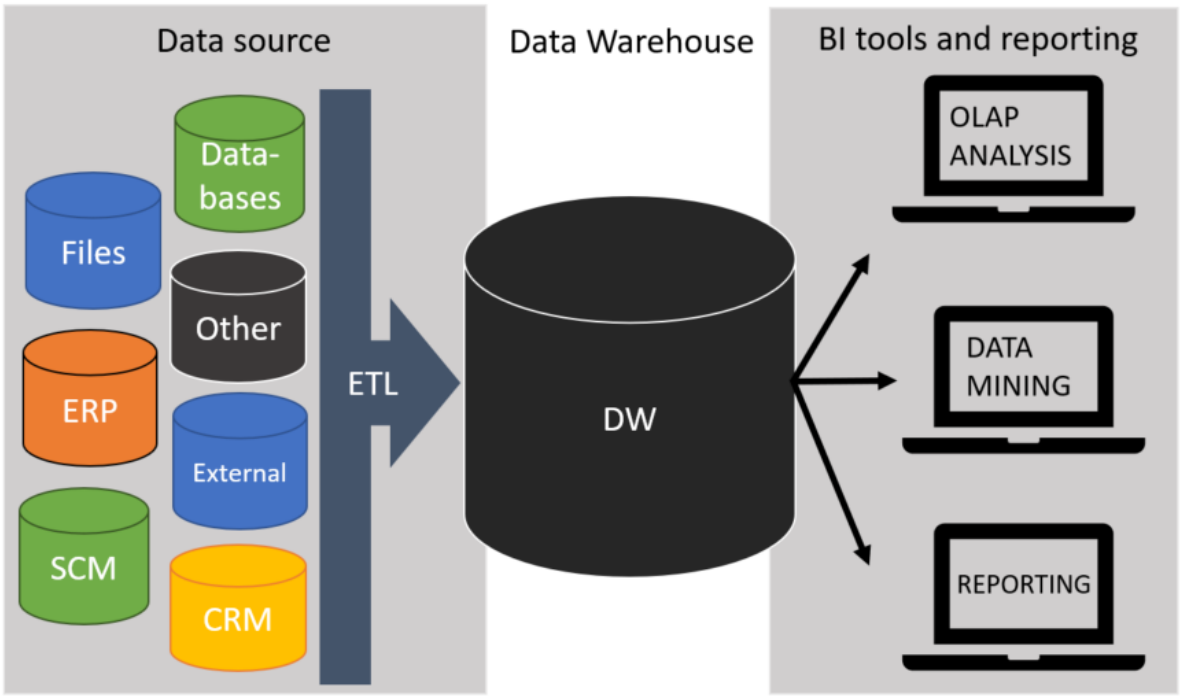

Figure 7: Basic Structure of BI architecture (Modified from Gordon, 2013, p. 142 and Chaudhuri et. al., 2011)

The basic structure of BI architecture is described in figure 7. Data Warehouse (DW) is considered to be a core component of BI. As electronic "storage" it collects and manages organizational transactional data from various sources, (Gordon, 2013, p. 141) like the ERP system, customer relationship management system (CRM) and supply chain management system (SCM), so that it can be exploited in organizational decision making. To be able to integrate required data automatically to the Data Warehouse and ensure the data quality it is essential to design prober ETL-process, which

- **E**xtracts necessary data from different source systems;
- **T**ransforms data to the proper storage format for the purposes of querying and analyzing;
- **L**oads the data to the final target database (Data Warehouse) (Nedelcu, 2013).

Once the data is stored to the Data Warehouse, it is organized so that all the data relating to the same event or other subject of interest is associated with each other and changes over time can be identified. As the data in the DW is integrated from operational systems of the organization, it is structured so that it is as a single collection of data. It is also nonvolatile as the data is never updated or deleted, once it is loaded to DW. (Gordon, 2013, p. 142)

When the data has been collected and integrated to the Data Warehouse, it is possible to exploit the data with BI tools, for example, benefiting Online Analytical Processing (OLAP) and Data Mining. BI tools enable to collect large amounts of structured and unstructured data from various sources and transform it for business use. Business Intelligence tools are often called Decision Support Systems (DSS) as they provide business users with tools to analyze their data and extract information. (Kopáčková & Škrobáčková, 2006)

OLAP is the technology behind many BI applications. It enables the performing of multidimensional analysis of business data interactively from multiple perspectives and producing reports, which allow users to track the status of transactions and providing meaningful views of past and present organizational data. (Nagabhushana, 2006, p. 9-10) Where a standard reporting tool can answer questions such as ”who...?” and ”what..?”, OLAP techniques have the ability to answer more sophisticated questions like ”what if...?” and ”why...?”. Since OLAP techniques are based around four basic operations that can be applied to a multidimensional cube of data, it allows to slice, dice, roll-up and drill-down the data (Gordon, 2013, p. 144) as shown in figure 8. It enables a better insight and understanding of business data that supports better decision making.

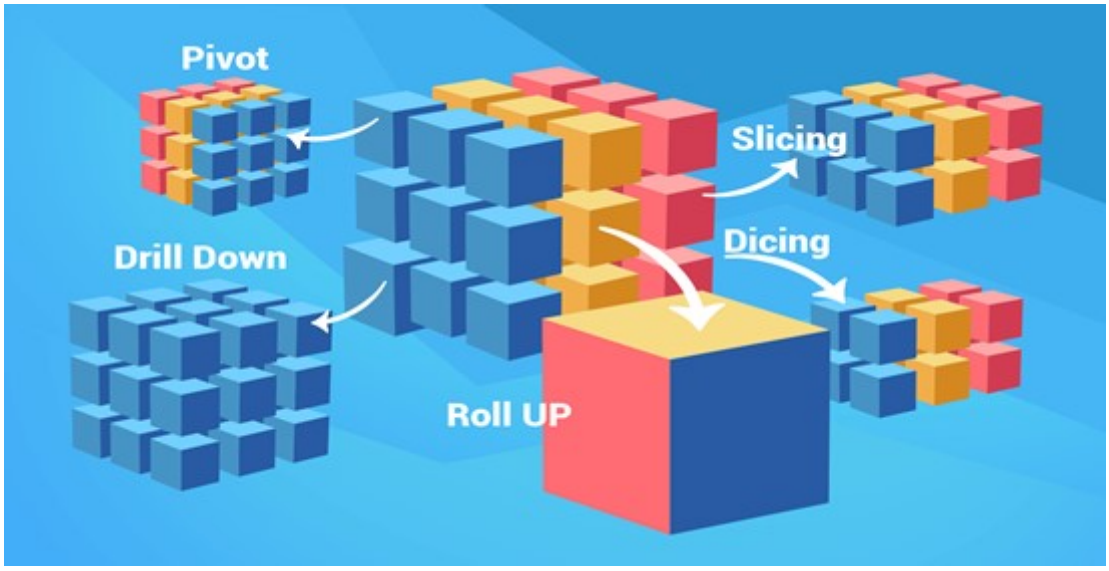

Figure 8: OLAP cube (Senturus, 2020)

Data Mining refers to advanced statistical and a broad range of other techniques, which aim to discover previously unknown patterns in large volumes of data (Gordon, 2013, p. 146). Its foundation comprises three intertwined scientific disciplines, as shown in the figure 9:

- statistics: the numeric study of data relationships
- artificial intelligence: human-like intelligence displayed by software and/or machines
- machine learning: algorithms that can learn from data to make predictions (SAS, 2020).

Data Mining enables the predicting of future patterns, identification and classification of data, as well as, optimization of data. It helps to explore the data stored in data warehouses and finds solutions for the certain business issues. The organizations can use it to turn raw data into a useful information. Data Mining is also known as Knowledge Discovery in Databases (KDD). (Clifton, 2019)

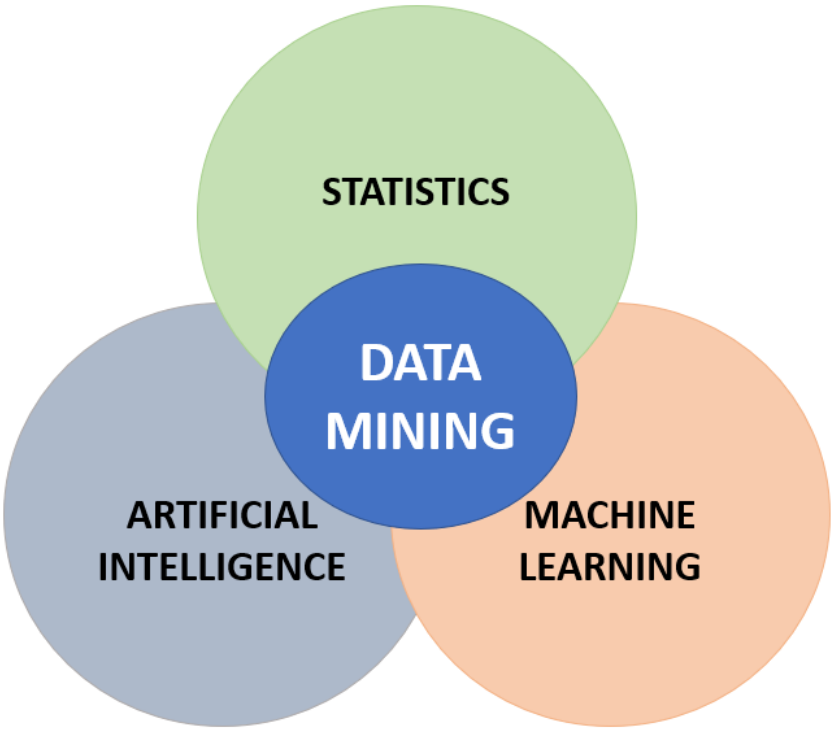

Figure 9: Foundation of Data Mining (Modified from SAS, 2020)

3.3 Decision Making

The world of decision making has dramatically changed over the last decades. The requirement of organizations to react faster to business variance, with less time to make decisions and find data to support the decision making. At the same time new data sources have become available for analysis and reporting (Van Der Lans, 2012, p. 1). This has also challenged the role of management reporting as the organizations needs to find solutions how to get the required data into one place and available for all decision makers.

Data is required for efficient decision making and up-to-date data generates more value and new opportunities for the organization. BI enables data-driven decision making (DDDM) as it allows the obtaining of analysed information from separate sources, classify and store the information (Laihonen et. al., 2013, p. 45). This is not only supporting organizational decision-making process, it also brings competition advantage.

Companies that are using data-driven decision making are more productive and more profitable than companies that are not using this (Singh, 2016, 32). However, in organizations all the important decisions are based on the information, that is available for the managers (Gordon, 2013, p. 3)

Traditionally organizations are measuring performance. Performance measures are designed to help people track whether they are moving to the planned direction and they help managers to establish whether they are going to reach the destination they have set out to reach. Decision-makers need to review the organizational data from different perspectives and different levels to be able to define the problems before they occur. On the other hand, they need information for detecting business opportunities to exploit. When an organization is systematically collecting and analyzing data of their own business and the business area where they operate, they can predict future outcomes and make fast change of directions. (Nagabhushana, 2006, p. 16-17) With effective and well-managed BI it is possible to obtain real time data fast and make changes quite rapidly.

Even though data-driven decision-making provides lots of benefits, there are also some challenges. Singh (2016) identified following challenges in the DDDM process:

- Broadness and complexity of data causes challenges in security, storing and processing of the data.
- Sources of the data determine which type of the data is collected and incorrect data in incorrect source causes incorrect decisions.
- Quality of the data
- Personnel analytical skills will affect accuracy, quality and efficiency of the analysis and decisions.
- Lack of appropriate tools and technologies
- Self-life of the data: Collected data is not processed and analyzed in timely manner and data will be outdated.

Data has a remarkable role in decision making, but BI cannot be gained with data or information alone. To gain “intelligence” it is needed to define what is relevant for the operations and future business. Business Intelligence cannot be accomplished without defined strategic goals and objectives. Key performance indicators (KPIs) are deriving from these goals. They help organizations to evaluate the current state of the business, its success and progress towards defined goals. (Sauter, 2011, p. 56) Establishing the correct KPIs is crucial as they should reflect your business. KPIs should be selected so that you can get followed data automatically out from systems, then it is much easier to implement them in the organization and they support DDDM efficiently.

4 Research Design and Methods

The objectives of the empirical research were to study the current practices, to identify the needs of improvements in continuous improvement and cost of poor-quality data reporting practices in the case organization and collect supporting data for theory building with attention on Business Intelligence. In this chapter, the research design and methodology applied in this study are described.

4.1 Research Methodology

The research is conducted as a qualitative case study, which followed action research methodology. Action research is aiming for transformative change through the simultaneous process of acting and doing research. It is based on problems, problem solving and community. The process can be seen as a spiral, where action, observation, reflection and re-plan follows in a cyclic process as shown in figure 10 (Heikkinen et. al., 1999, p. 36). The changes to the problematic process will be carried out one by one and change will occur after repeating the cyclic process several times. In this context, action research can be also seen as a systematic learning process.

The action research methodology is both participative and reflective, and it is tightly integrated to a work or development situation. It is probably the most effective known method for handling complicated problems in the arrangement of work (Rautio, 2007). The action research starts with the study of everyday work, situation, human activity and mapping. It starts from a description of the activities under research, but the focus is on cooperation between the researcher and the subject. Action research is usually conducted in organizations to improve the quality of the organization and its performance. In this context, developing the functions can be seen as a continuous improvement.

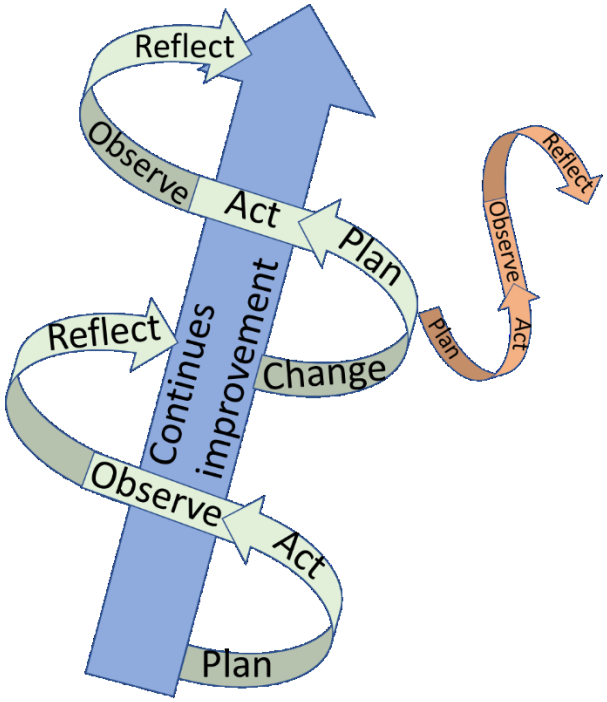

Figure 10: Progressive action research spiral with side spiral. (Modified from Heikkinen et. al., 1999, p. 37, 39)

Although, the action research is always cyclical, there are different models, how the action is proceeded. The first model is an iterative process model, where detecting the problem and action alternate until a solution is found to the problem. The second process model is linear. It focuses on experimenting and evaluating individual intervention. The third process model is reflective. It examines the activities of people and the link between their approaches, with the aim of solutions to the problems arising from operations models. (KAMK, 2020) This research was following the iterative process model.

Even though, action research is described as a progressive and forward going process, in reality organizations and work communities have so many related processes on going at the same time that they can rarely be combined into one onward spiral. In the beginning of action research, it might be unclear what problems and questions occur during the study. It is typical that during the development process a minor problem or side question generates new side spirals and a change of direction as shown in figure 10. (Heikkinen et. al., 1999, p. 38-39)

The researcher is actively participating in the change process by solving the practical problem and collecting research data at the same time. Even though the researcher is working in the organization during the research, he or she has rarely enough previous knowledge about the operations and problems to estimate and explain them. This is why it is relevant to engage employees in the development work. The researcher brings the general theoretical knowledge and skills available for the work. (Rautio, 2007)

When action research is conducted in a case organization, three phases can be identified:

- Getting into the organization
- Conducting the research
- Finally exiting the organization. (Irvine & Gaffikin, 2006)

The first phase, getting into an organization, can be problematic for the researcher (Irvine & Gaffikin, 2006). In this study the researcher was already working in the organization, so getting into the organization was not causing problems. In addition, when the researcher is already part of the organization, he or she does not have the possibility to finally exit the organization either. Quite often this is crucial for the research, because distance enables the researcher to examine the research subject and collected data more critically (Irvine & Gaffikin, 2006).

4.2 Data Collection and Analysis

The research data was collected from the organization through semi-structured interviews, observation and analyzing organizational documents. Data collection followed the cyclic action research process with action, observation, reflection and re-plan.

The data for literature review was collected mainly from the Internet with the aid key words. The sources for literature review consist of scientific articles, previous research and other publications.

As the collected research data was mostly qualitative, the used analysis approach was inductive. Analyses were conducted regarding the current state study, case study and action research. To ensure the accuracy of the conclusions, all the analyses and conclusions were reviewed with key personnel of the case organization.

5 Case Organization

The organization is a global developer and supplier of lifecycle solutions based on high-quality products, processes and services. It is developing unique technology and innovations to drive the performance of its customers. The organization has a long history of delivering large and complex industrial machines and sites around the world.

The organization is committed to high quality in their operations, products and services, which they provide to the customers. They are targeting excellence in processes which includes the promise to keep improving the quality performance constantly. The main target of quality operations is to improve quality performance and ensure customer satisfaction. To improve the quality of their products, processes and services, they are focusing on improving the quality culture, developing the way they operate and how they work to reduce quality costs. They have a strong focus on improving their quality based on continuous improvement and Lean practices.

The organization has achieved growth through many acquisitions during previous decades. Currently it includes four business lines, which are focused on different industrial sectors. They are organized in five geographical areas: North America, South America, EMEA (Europe, Middle East and Africa), Asia Pacific, and China. The organization has gained a strong market position in all its businesses.

In this research we are focusing on developing the functions of one business line and specific business unit. However, the results can benefit the whole corporation and can be utilized for its other lines and areas.

5.1 Drivers of Change

In 2015, the executive team of case organization decided to implement a business transformation project across the whole corporation. It was aiming to bring people, process and technology closer to its business strategy and vision. One remarkable driver for the

change was digitalization and the requirement for efficient digital tools. One of the main focuses was to renew the ERP tools of the company and harmonize its ways of working. It was a starting shot for many development projects and transformation programs, which all were targeting on harmonized global processes and one ERP system.

Originally the organization had over twenty ERP tools in use due to its growth through many acquisitions during previous decades. From an operational perspective it means that master data is fragmented to several systems and multiple data sources must be integrated. Data harmonization is a prerequisite for being able to operate in one global common ERP system.

The renewal does not involve only the ERP system, but additionally all the other surrounding applications. The whole transformation program is heading to digitalization and effective ways of working by improving the operational processes behind project and service deliveries, so that they can be closer to their vision of becoming the global champion in serving customers. This means that also internal processes must be examined and developed to gain excellence in processes and a Lean way to work. One of these processes is continuous improvement and integration of the cost of poor-quality data, which we studied in this research.

5.2 Current Practices

In the case organization, financial reporting comprises both public external financial reporting and management reporting. The role of financial reporting is to provide on time, reliable, consistent information of financial performance, of the organization, to its shareholders, investors and other stakeholders. Management reporting provides monthly financial information for the Board of Directors, Business line management and other internal customers. Management reporting includes, for example, monthly reports, monthly comments and other special information such as capacity costs, quality costs, IT costs and other function costs. In addition, the responsibilities include facilitation of

the monthly estimation process, planning process for the next financial year, as well as, supporting the strategy process of the organization, from a financial perspective. The target of management reporting is to provide management with relevant, reliable and up to date information about the financial situation of organization.

As the case organization is committed to high quality, the cost of poor-quality data is one of the most important key performance indicators. Quality costs indicate the degree of quality of processes, products and services. Costs of poor quality (COPQ) are all those costs, which will arise, if the things are not done right the first time and thus the expected demands are not fulfilled. Collecting and analyzing costs of poor quality makes the concept of quality more concrete, highlights the problem areas and prioritizes needed corrective actions. By reporting the costs of poor quality, improvement opportunities can be identified, and the recurrence of problems prevented.

In a case organization a measurable target is to reduce quality costs down to a defined percentage of net sales. Business lines and geographical areas are responsible for gathering and reporting the cost of poor-quality data on a monthly basis. In the organization, the basic purpose of COPQ reporting is to support continuous improvement through the use of quality incidents and quality costs as a tool to identify improvement opportunities and to prevent the recurrence of problems.

Even though the primary tool for COPQ data collection is the ERP system, data is spread out in separate files and databases. Currently the organization has several tools in use and under development for quality management, analytics and reporting, which causes a lack of unclarity among employees. A portion of information is in ERP systems, but some still remains in excel format. For example, project sites have rarely ERP system connections and alternative reporting channels are needed. Currently, the analyzing of COPQ data is not at a required level and without applicable reporting tools this KPI is complex and causes lot of manual clarifications and studies.

A remarkable challenge in collecting COPQ data is that the continuous improvement process and feedback collection is not handled in the ERP system. Costs are reported in the ERP system and feedback is collected in another application. The organization has a global continuous improvement application in use, which target is to harmonize the feedback and development processes by establishing a common place for proposal creation and management. However, currently the continuous improvement application and ERP system do not have two-way integration, and that is why combining the costs actually generates lots of manual work. It also causes lots of unclarity among employees, because they are not aware of how and where to report COPQ. When the current systems are not supporting the reporting as they should be, costs of poor quality are reported incorrectly, or they are not reported at all. Monthly reporting of COPQ is time-consuming and requires lots of manual work as the data is scattered several systems and locations. Key persons estimated, in preliminary interviews, that reporting of COPQ in one business line takes approximately 30 hours on a monthly basis.

In the organization, quality costs are categorized into main categories and problem areas based on the root cause. To be able to reduce quality costs down, it is important to find the actual root causes and affect to them. Currently, the majority of root causes are reported in the category “Responsible code missing” which is not supporting the organizational target setting.

As the organization is strongly focusing on providing value to the customer, it has also been affecting their Business Intelligence. When the organization is mostly focusing on external data and developing intelligent solutions for customers, developing internal processes and ways of working have received insufficient attention in many fields. One good example is in the cost of poor-quality data reporting, which cause lots of manual work monthly basis, even though the organization have proper BI tools available. The case organization was currently implementing Microsoft Power BI. It is the selected software for a new global reporting tool, which will eventually replace currently used tools.

Limited development resources concerning internal processes and ways of working are remarkable challenges in the organization.

6 Empirical Case Analysis

The research was conducted as an action research between April 2019 and December 2019 in the case organization. Before initiating the research project, the researcher observed the case organization, studied current practices and conducted preliminary interviews to identify key challenges of management reporting and data management. Even though the researcher was already working in the organization, she had no experience of COPQ procedures and was not able to estimate and explain them in needed level. Therefore, it was relevant to engage with key persons in the organization with experience of quality issues and COPQ development work. As the project was aiming to create automatized and digitalized reporting, it was also essential to have a Power BI expert on the board of the project team. As mentioned earlier, the case organization was recently implemented Microsoft Power BI, so it was the natural selection for this project. As the IT department of the case organization had limited resources of Power BI, an external information technology (IT) partner was required for the project. In the early phase, the project team were launched, and it consisted of

- Key persons in the case organization, who had experience of quality issues and COPQ
- Power BI expert (IT partner)
- Development Manager from enterprise analytics (IT)
- IT Service manager, reporting (IT)
- Data engineer (summer trainee, who worked from April to August)
- Project manager (the researcher)

The research was conducted as action research, which can be seen as continuous improvement and learning process, where action, observation, reflection and re-plan are repeated, as long as desired change occurs. Next, we will examine this project from an action research perspective and describe the changes phase by phase from a BI architecture, reporting, data management and change management perspective. Some of these development phases were overlapping, for example developing the reporting and

creating BI architecture. However, every development phase included the same procedure: After the changes, the project team piloted, evaluated them, made re-plans and new actions.

6.1 BI Architecture

Creating the Business Intelligence architecture for COPQ reporting followed the cyclic process of action research. In the first development phase, the connection between the ERP system and Microsoft Power BI was created as shown in the figure 11. COPQ data was collected in the ERP system and it was integrated to the DW by using the ETL-process. The organization had developed the ETL-process and Data Warehouse earlier and they were already in use. Therefore, it was a straight forward process to get COPQ data from the ERP system through the DW to Power BI enabling online reporting. However, one target of this project was to integrate feedbacks and costs to one report. This first phase enabled to bring only ERP data with the costs to the report.

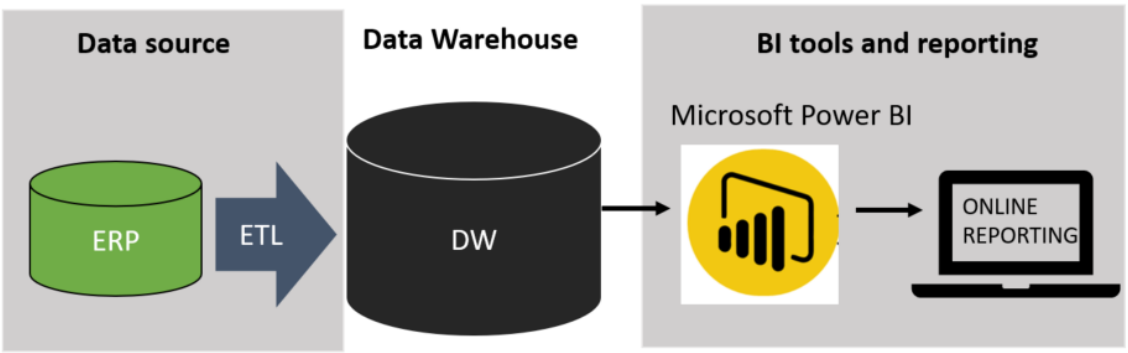

Figure 11: The first phase of the Business Intelligence architecture. COPQ data from ERP.

As described earlier COPQ, were reported in the ERP system, but all feedbacks were collected in another application and there was no integration between feedback application and ERP or even DW. Therefore, in the second development phase a connection from the feedback application to Power BI was created. As the feedback application was built into the collaboration platform, the connection needed to be carried out through

application programming interface (API) as shown in the figure 12. API is an interface or communication protocol, which enables different applications to make requests and change data, in other words, communicate with each other. In this case, we used API to bring defined data from the feedback application directly to Power BI. This is how we managed to integrate ERP and feedback of COPQ data. With these two development phases the required architecture was created.

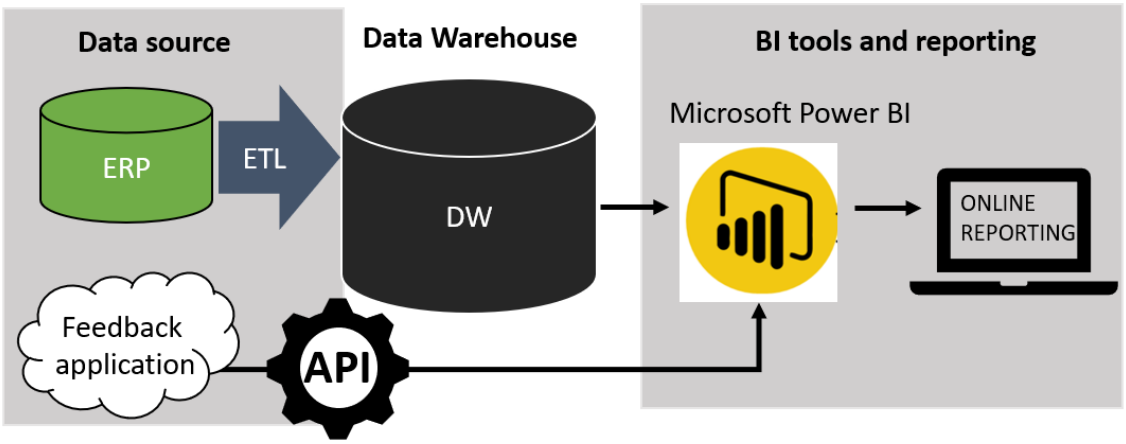

Figure 12: The second phase of the Business Intelligence architecture. Feedback application has been added.

6.2 Reporting

The development of COPQ reporting followed the same phases than BI architecture. As there was only ERP data available in the first phase, development work concentrated on visuals of COPQ data and creating Power BI dashboards. Preliminary interviews and study of earlier reports showed that management of the case organization had a good knowledge of COPQ reports and level of reporting. Therefore, existing reports were used as a model for Power BI dashboard creation. Developing the reports and dashboard turned out to be continuous improvement process as they were changed many times during the project. Figure 13 shows the idea of the created COPQ dashboard. It includes the following information:

- COPQ by Cost Category
- COPQ by Problem Area (PA)

- COPQ by Project
- COPQ and PA code % trend
- COPQ Year to date (YTD) and Month to date (MTD)
- Reported transactions MTD
- Problem area code exists/missing

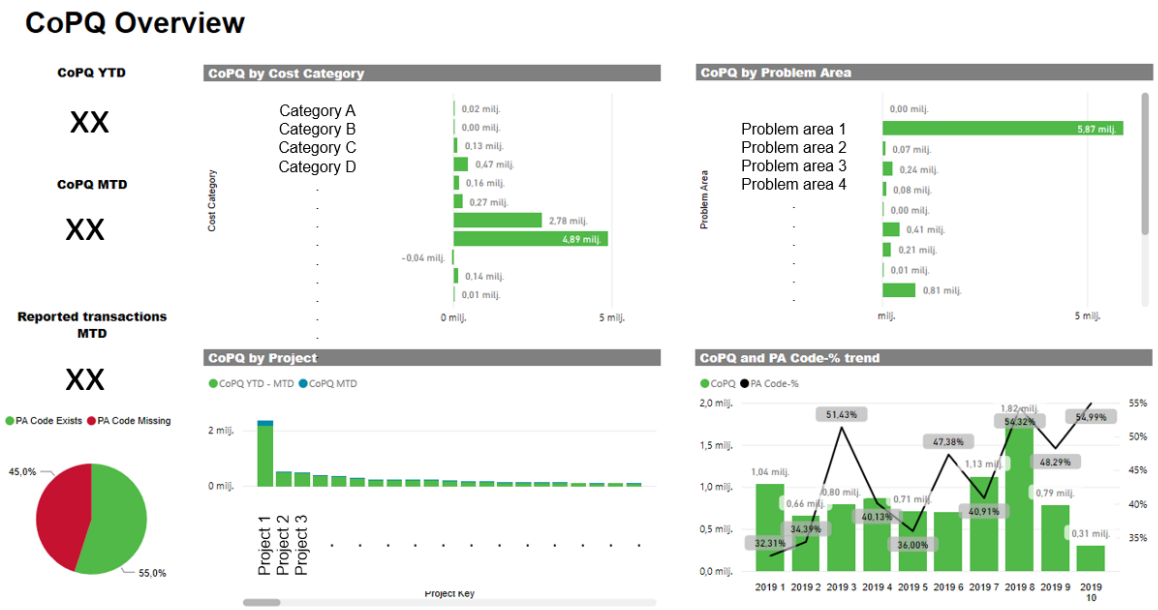

Figure 13: Power BI dashboard

In the second phase, data from the feedback application was transformed into Power BI. In this phase only predefined limited data was transformed, because the existing data volume was so massive that it might cause problems in the application programming interface. The data was restricted to concern two pilot projects and five key columns: feedback ID, project name, warranty work number, cots category and problem area coding. After testing the report, it was noticed that drilling into feedback data was required and required adding the links to the feedback application. In the third phase, hyperlinks of feedback IDs were added which enabled detailed study of feedbacks and root causes as shown in the figure 14.

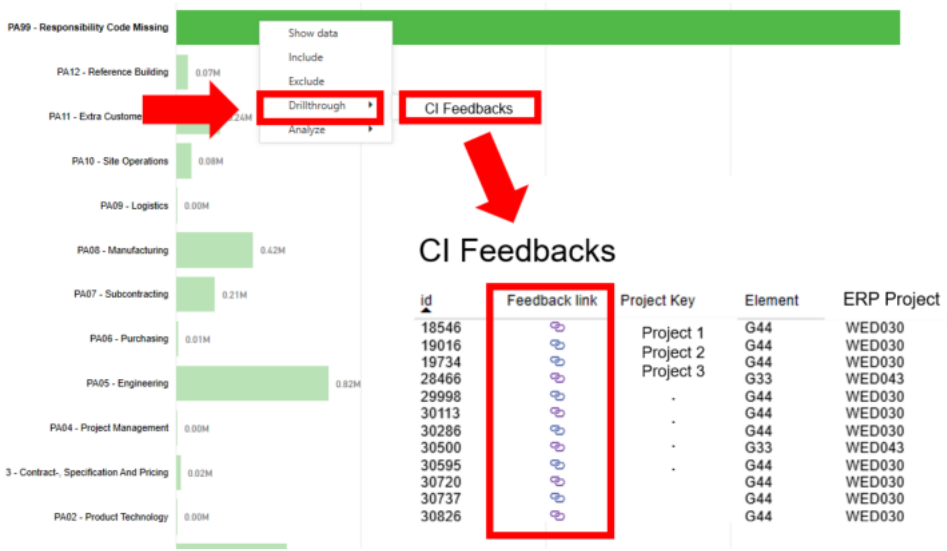

Figure 14: Links to the feedbacks and feedback application have been added to the Power BI report

In the fourth development phase, it was noticed that COPQ by the technology group is relevant for business reporting. The organizational operations are very strongly focused on technology groups and it is essential to study the COPQ monthly bases also from this perspective. Therefore, the specific sheet for COPQ by technology group was created as shown in figure 15.

After piloting the report, it was noticed that more data is required. In the final development phase, the following columns were brought to the report from the feedback application:

- Reporting date
- Estimated cost of IA (Immediate actions)
- Estimated cost of IA Currency
- Actual costs
- Actual costs currency
- Refunded costs
- Refunded costs currency

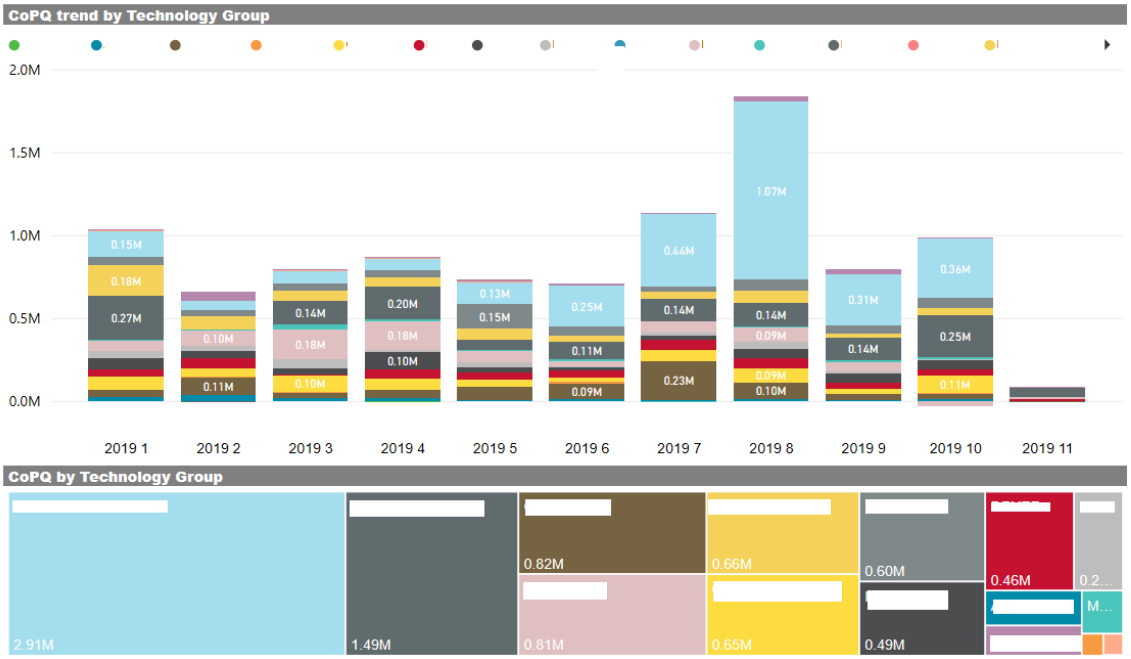

Figure 15: Specific sheet for COPQ by Technology group was added to the Power BI report

6.3 Data Management

The created Power BI dashboard made it possible to examine the data quality of COPQ on more detailed level than ever before in the case organization. On the other hand, it raised up many problems in data management.

In the first development phase, when the COPQ data was collected from the ERP system and brought to the Power BI report, it was noticed that data is not reliable as it is not totally complete. Even the COPQ should have been reported to the ERP, the process was not followed properly in every case and the data was insufficient. The same challenge occurred also in the following development phase, when the data was transformed from the feedback application to the BI tool. It was not only making data unreliable, but also complicated data integration.

A remarkable challenge for data integration was data quality as the project numbers were not registered properly to the feedback application. Although, the only way to

integrate transactions between the EPR system and the feedback application is the project number / warranty work number. Especially problematic were small site projects, which do not have the same procedure for opening project numbers with prober coding as the big projects have. For example, in August 2019 site operations registered 43 feedbacks concerning one pilot project and only six of them contained proper quality markings and project information. In the other words, in 37 cases it was not possible to integrate the ERP data and feedback because of insufficient registration.

Another obstacle for successful data integration was that project number / warranty work number was generated in multiply different formats in the feedback application. This derives from the fact that field of the project number was not guided, and it allowed multiple variations. To be able to build the integration and get reliable reporting out of the system, it required that Data Engineer was maintaining the data and constantly reminding project managers about the proper registrations of COPQ.

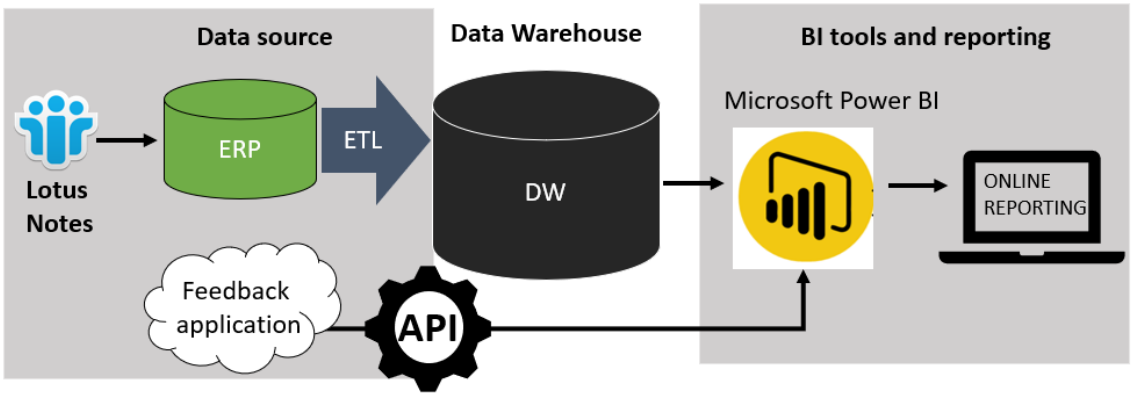

Figure 16: Existing integration between Lotus Notes and ERP.

The case organization uses multiple different applications and programs relating to the ERP system, which causes challenges for data integration. In big projects warranty work numbers are still opened in the Lotus Notes Database and there is an integration built to the current ERP as shown in figure 16. However, successful data integration requires that all the fields showed in the figure 17 are filled properly in the Lotus Notes Database or

otherwise data will not be transferred to ERP correctly. During this research it was noticed that, for example, an estimated cost was missing quite often, which is why problem area codes were not transferred correctly to the quality marking report and to the Power BI dashboard.

	Reason	Estimated Cost (EUR)	Classified Reason For Warranty Work	Problem Area
1.1	Steel was not prepared for painting prior painting by chinese subcontractor	100000	Reason x	PA 05

Figure 17: Required fields for successful data integration in Lotus Notes Database

6.4 Problem Area and Root Cause Coding

As the preliminary interviews showed the organization had a need to provide reliable reporting of COPQ, with proper problem area and root cause coding in order to reduce quality costs and to achieve the targets. However, the majority of root causes were reported to the category “Responsible code missing”. A deeper study showed that the site projects are opened to database, they mark automatically the code PA99 “Responsible code missing” to all new cases. After this it is responsibility of project manager to change the code according to the actual root cause. However, in most of the studied cases the codes were not changed accordingly.

As the figure 18 shows, in the years 2015 - 2017 over 50 % of all the reported COPQ cases did not have proper coding and it was not possible to dig into the real root causes. It seemed that there would not be any progress in the year 2019 either without maintaining the data and starting the manual data management process.

In November 2019, the manual data management process concerning PA-coding was launched. As the temporary Data Engineer had already left from the project, the researcher as the project manager, took over the data maintenance and engaged the responsible persons to the work. All the COPQ with the code PA99 were reviewed and

project managers were asked to register the real root causes. The codes were fixed manually to the ERP system. This manual coding process reduced PA99 percentage from 58 % to 16,6 % as marked in the pattern fill in the figure 18.

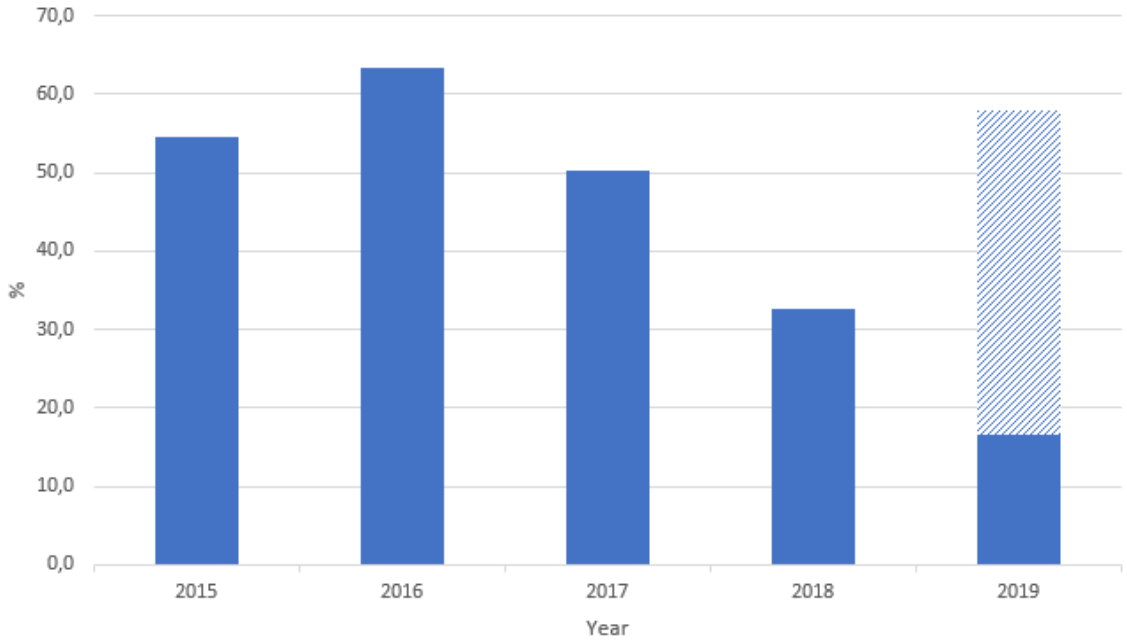

Figure 18: PA99 percentage of all COPQ by year

Right after the manual coding process, incorrect kinds of deviations were observed in the Power BI report and sudden increase in COPQ. Deeper investigations revealed an error in the Data Warehouse logic. It distorted the COPQ data from ERP and doubled all the manually coded cases. After the IT vendor fixed the logic, reporting restored to the correct level. Without visualization, the data and created Power BI report, the problem could have continued unobserved.

6.5 Change management

The change management process was targeting to support and help individuals and teams in making change of their current practices and ways of working in a case organization. The process focused on increasing understanding of COPQ process among employees and manually coding the problem area and root cause coding. It was targeting

to raise the awareness of Business Intelligence and importance of collecting, analyzing, processing, storing and delivering real-time information for the needs of organizations. One of the key issues was also understanding of data quality in efficient decision making. The process was aiming the transformative change through the simultaneous process of learning, acting and developing. It required teaching and engaging people constantly, as well as, changing daily priorities and ways or working.

One of the remarkable phases in change management process was understanding of COPQ and accurate reporting of COPQ. The project managers had a key role in this change as the earlier described manual coding process showed.

7 Results

The research was carried out in a case organization as a multi-method qualitative study, which followed an action research methodology. Preliminary observations and interviews reveled challenges in the COPQ practices and management reporting. Based on the preliminary study the case organization needed to have a more user-friendly, reliable, visible and on-line data-based way of working, which enables to get the processed cost of poor-quality information out from one channel without manual work. Better integration between ERP data and CI data were also required to provide reliable reporting of COPQ with proper problem area and root cause coding.

Even though, the research followed the cyclic process of action research, it included four subprocesses (figure 20), which were targeting to development of management reporting to guarantee efficient Business Intelligence (RQ1) and to automatize handling and visualization of data from different systems to help improvement and analytics:

- BI Architecture
- Reporting
- Data management
- Change management

All these subprocesses followed the iterative process model, where detecting the problem and action alternated until a solution was found to current problem. The research generated user-friendly, visible and on-line data based COPQ reporting by using BI tool Microsoft Power BI. It enabled an automated and digitalized COPQ management reporting with several dashboard views. As a part of BI architecture process an integration between the ERP and the feedback application was created by using API and benefitting the existing Data Warehouse and ETL process. It provided reporting of COPQ with proper problem area and root cause coding.

Data management process concentrated on a development of COPQ data collection and integration, and revealed the problems in data quality, as well as, ways of working. Therefore, change management process focused on increasing understanding of COPQ process among employees and manually coding of the problem area and root causes. One remarkable data management development phase was the manual coding process. It reduced the root causes, which were reported to the category "Responsible code missing" from 58 % to 16,6 % as marked in the pattern fill in the figure 18. The manual coding process revealed that the most remarkable root cause of COPQ is problem area 5 along with two other major causes are problem areas 1 and 2 as figure 19 illustrates.

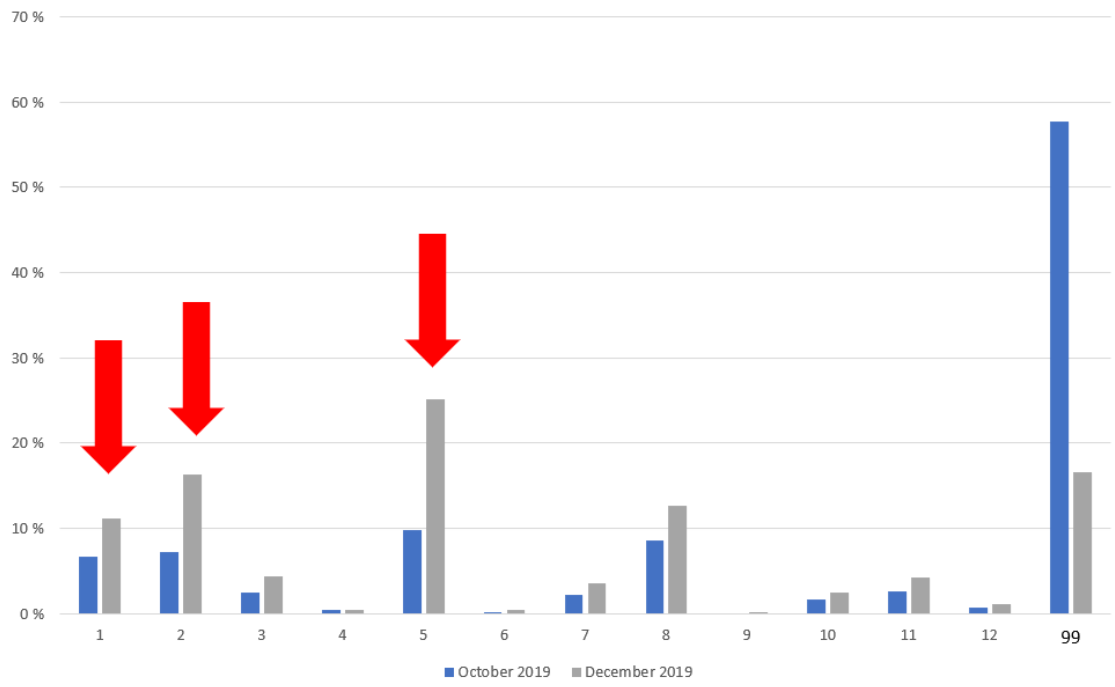

Figure 19: Root causes after manual coding process

Data management process with created Power BI report also indicated incorrect deviations in visuals and revealed an error in the Data Warehouse logic, which was distorting COPQ data.

As a result of this research the continuous improvement of the case organization and the cost of poor-quality data reporting practices were improved. Figure 20 summarizes the

results of the research. With this research we found solutions for the problematic processes of the case organisation in CI and COPQ data integration from management reporting perspective and promoted change within the organization. Automatized, visual, online data-based, user-friendly COPQ management report with ERP and CI tool data integration benefitted the case organization in many ways, but revealed also some challenges, as shown in the figure 20.

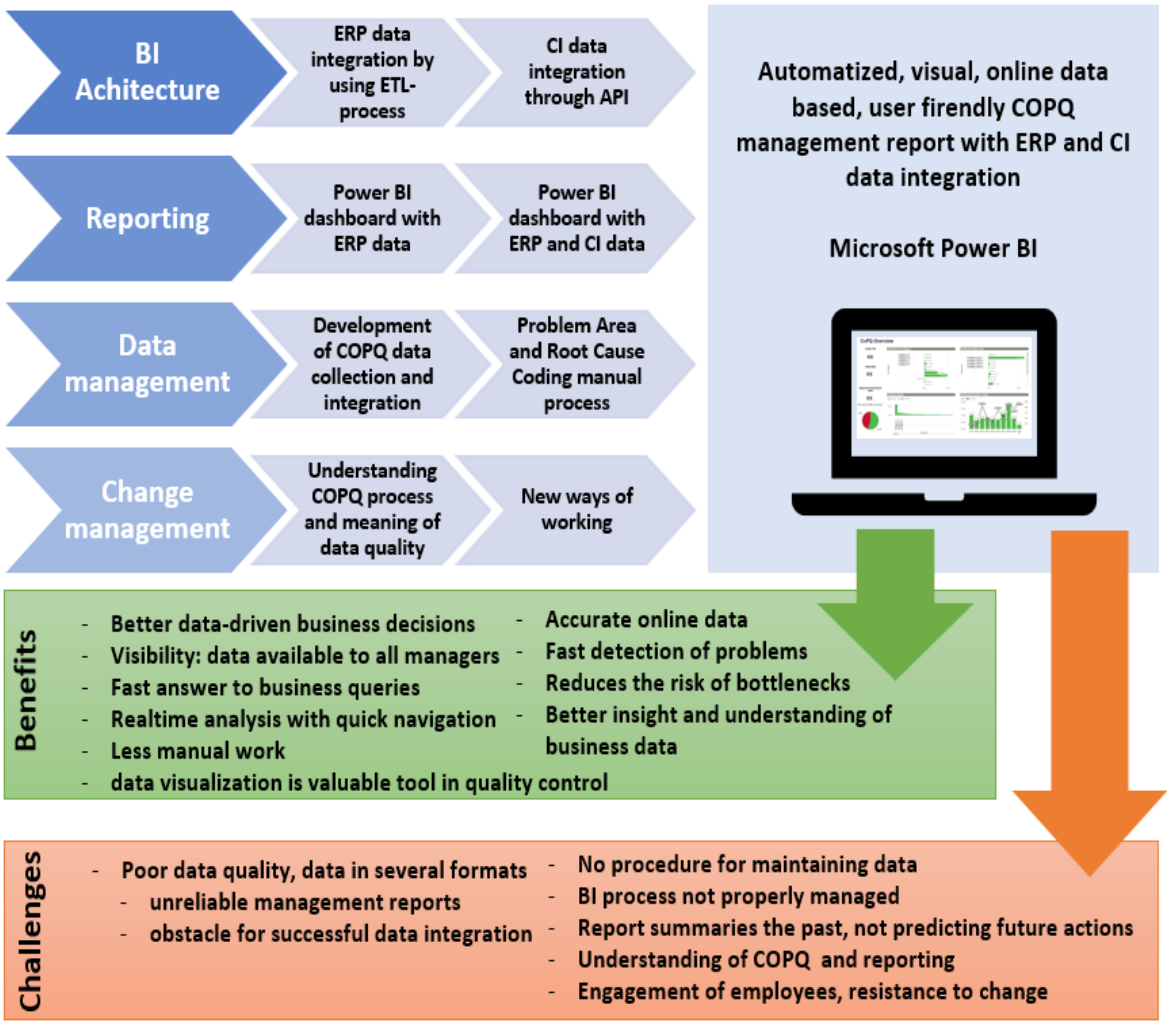

Figure 20: Results of the research.

This action research was aiming for transformative change through the simultaneous process of acting and doing research in the case organization. It was based on problems, problem solving and community. With this development project we managed to bring

people, process and technology closer to business strategy and vision in the case organization by raising awareness of COPQ, automating reporting with BI tool and adding visibility.

8 Discussion

Business Intelligence is targeting to collect, analyze, process, store and deliver the real time information for the needs of organization to assist managers in decision making. BI solutions, on the other hand, enables efficient and automatized reporting, when on-line data can be collected from several data management systems and transformed into useful information for organizational decision making. However, data quality has a remarkable role in this process. Even the most efficient BI tools are not able to generate reliable reports from bad data. In organizational decision making it may lead to wrong analysis and predictions.

This research was aiming to develop organizational reporting to guarantee efficient Business Intelligence (RQ1), automatize handling and visualization of data from different systems to help improvement and analytics. As the preliminary interviews showed, the case organization wanted to have an automatized and digitalized reporting system, which allows the obtaining all processed COPQ information out from one channel without manual work, and to have better integration between ERP data and continuous improvement data, as well as provide reliable reporting of COPQ with proper problem area and root cause coding. The research was focusing on developing reporting with BI tools and generating user-friendly, reliable, visible and on-line reporting. The approach was very technical oriented, which is typical for technology companies. They are looking for a technical solution to the appeared problem, but not trying to fix the root cases behind the problem: problematic practices, ignorance and wrong ways of working.

8.1 COPQ Dashboard and Reporting

During the research, a required COPQ dashboard was created with Power BI. Required integration between the ERP and the CI feedback application was created by using API and benefitting the existing Data Warehouse and ETL process. The architecture enabled the creation of the BI dashboard with user-friendly, visible and online data reporting. However, it still has challenges with reliability. According to this research, it was

observed that even fancy BI tools are not able to generate the reliable reports, if the collected data is not high quality. The created Power BI dashboard and reports are not able to produce reliable management reports, if the data is not filling the business data quality elements like Drăgan and Metz (2017) stated: accessibility, credibility, accuracy, consistency, completeness, integrity and readability. In the case organization there were problems especially in accessibility, accuracy, consistency and completeness, as the data was spread across many systems and it was not reported properly in the correct format.

According to this study, data visualization can be valuable tool in quality control as it reveals errors in data and data collection immediately. During this study, incorrect deviations were observed in visuals and in sudden increases of COPQ right after manual coding process. Deeper investigations revealed an error in the Data Warehouse logic, which was distorting COPQ. Without visualization of the data, the problem may not have been noticed so rapidly. It was also a good reminder to the organization that information systems must be controlled and tested regularly. The organization cannot trust systems blindly, they need to also control the quality of their IT-systems.

The created Power BI -report summarizes what has happened over a certain period and focuses on one key performance indicator. To gain business advantage, the reporting should be changed into a more analytical direction and instead of summarizing the past, the focus should be on predicting future actions. However, there is no point to develop COPQ Power BI reporting any further, until the data quality has been ensured.

8.2 Data Management

According to this research, bad data is not just producing unreliable reports, but it is also an obstacle for data integration. If the data is in various formats in several systems, it is impossible to integrate. In this project we had problems with integrating ERP and CI feedback data as project numbers were typed in multiple formats in the feedback application. The same challenges occurred also between Lotus Notes and ERP.

Before the data quality can be improved, the data and the needs of data must be comprehended. According to this study, the case organization has not yet totally understood the meaning of the data and required actions, which produce the information and knowledge. However, data value is created by gaining an understanding of the data and improving the data accordingly where deviations are found. It requires collaboration through the entire organization and data management must be responsibility of everybody. Processes must be well defined and properly instructed so that every level of the organization knows how to deal with the data and how to ensure data quality. It is also matter of change management.

As the case organization does not have procedure for maintaining COPQ data and it has not yet established a way of working among its employees, the role of the Data Engineer needs to be defined. During this project, a temporary Data Engineer was working, and it is recommended to have the same role with following duties in the future:

- Managing and organizing data
- Carrying out transformation tasks on data – data cleansing and validation
- Ensuring data quality (Work numbers, PA codes, costs etc.)
- Transforming data into a useful format for analysis
- Guiding the organization reporting procedures
- Developing ways to improve data-driven processes and information sharing
- Identifying ways to improve data reliability, efficiency and quality
- Using data to discover tasks that can be automated

Before the case organization can benefit the BI, it must make sure that it is collecting relevant data in correct format and it has a defined process. Business Intelligence brings value to the organization only when it is properly managed and in a systematic process. Especially the case organization should take note of this in evaluating information quality, reliability and usability, as well as, monitoring utilization of information and how well it is fulfilling the information needs. To be able to guarantee efficient Business Intelligence it must be properly organized and responsible persons must be defined. At this point,

ensuring high-quality data should be prioritized in the case organization. Although it is a business issue, but above everything, it is a management issue. It is also change management issue as it involves collaboration between all employees, from entry-level to top-management. However, the case organization still needs to learn that data must be processed into information and knowledge until it supports a data-driven decision-making process and it is beneficial for the organization.

8.3 Usability and Attractiveness

During the research, other business lines of case organization also showed interest concerning Business Intelligence and benefitting from Power BI reporting. They were especially interested in creating API between the ERP system and the feedback application as they have not had any two-way integration before. However, this research concerned only a very limited amount of data: COPQ data of two pilot projects. If they are planning to extend the integration to other fields, it must be considered changing the architecture to guarantee adaptable and reliable use, for example, building a database or Data Warehouse between these two systems. However, more suitable longer-term solutions would be integrating the feedback application to the ERP system as shown in figure 21.

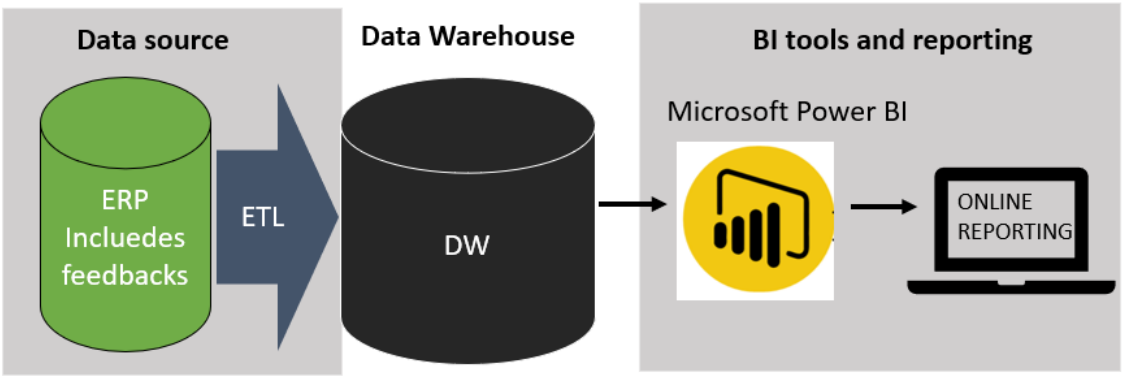

Figure 21: Integrating the feedback application to ERP.

As mentioned earlier, this research project derived from a transformation project of case organization, which was aiming to achieve one global ERP system. When the research started it was expected to have the new ERP system in use in a few months. However, the implementation of this new ERP system has been postponed several times and therefore this research was conducted with old ERP data. The created Power BI report will benefit also future needs as the new ERP will also use the same DW and the data management process will be similar. Although, it would be a good time to consider creating corporation level instructions of COPQ collection and reporting. It seems that there are various ways to achieve this even in one business line and there are too many different databases involved causing errors in data integration.

8.4 Measurable Targets

Measuring conducted transformation actions is crucial in change management processes. For the organization it is important to find out how they benefitted the conducted actions and what kinds of improvement has been gained. When this research was launched one of the organizational key targets was to provide reliable reporting of COPQ with proper problem area and root cause coding. However, as the created BI report visualized, the majority of root causes were reported to the category PA99 “Responsible code missing”, which is not helping future target setting and the digging into of real COPQ root causes. Therefore, it was essential to launch the manual PA coding process. As a measurable target, it reduced the PA99 coding percentage remarkably from 58 % to 16,6 %. The manual PA coding process also established major COPQ root causes were problem area 5, as well as problem areas 1 and 2. To be able to achieve the strategic goal in the case organization and reduce quality costs, these three problem areas are where special attention is required in the future.

Another measurable object of this research was reporting time. After implementing the new way of management reporting in case organization, key personnel estimated that it could save 30 % of their time. However, this cannot be achieved until data quality is at a

proper level and the generated Power BI report is reliable. Released time can be used for analyzing the data and supporting the decision-making process of the organization.

8.5 Generated Side Spirals

It is typical in action research that during the development process new problems or side questions generate new side spirals, as happened in this case. During the research, three side spirals occurred as shown in figure 22.

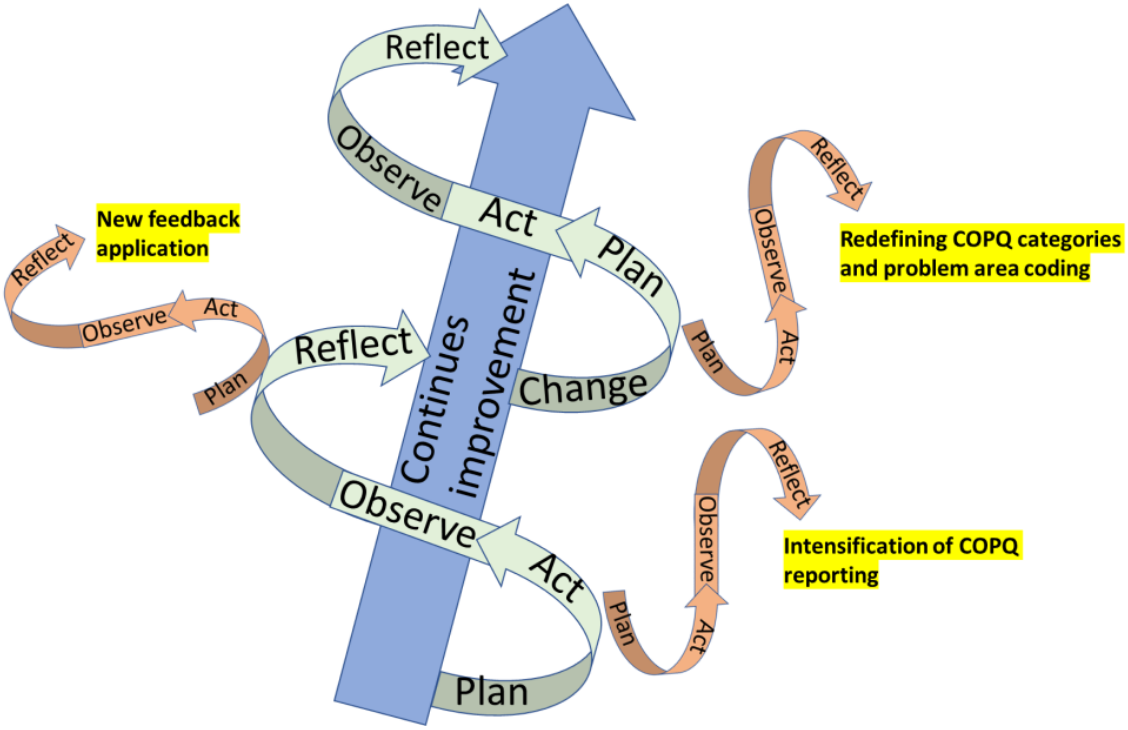

Figure 22: The research generated three new side spirals. (Modified from Heikkinen et. al., 1999, p. 37, 39)

During the research, it was noticed that reporting of COPQ is not at a required level in the case organization. Reporting showed the root causes are incorrectly registered and they required special attention. More COPQ actually occurred than was reported. The problem generated new side spirals, which is aiming for the intensification of COPQ reporting. It is aiming to establish real root causes and reduce the COPQ. This side spiral follows the manual PA coding process.

The other side spiral concerns the development of the COPQ problem area coding. At the corporate level they started a conversation, whether categorizing of COPQ and problem area coding should be renewed. According to this research, the questions is relevant as too many COPQ are reported as code 99 “Responsible code missing”, and root causes cannot be defined. However, COPQ data is one of the most important key performance indicators in the case organization and their goal being to reduce quality costs. Without changing the coding procedures and blocking the use of code 99, they are unable to drill to the root causes and achieve the target.

The third new question was the use of feedback application. The biggest challenges seemed to be that the feedback application was not integrated to other systems and it was not well-known among employees. Its usability was questionable in many development phases during this research, and the problem has also been noticed at the corporate level of case organization. Therefore, they started a development project, which is aiming to find a new more integrable feedback tool.

9 Conclusion

The research was aiming to clarify how organizational reporting can be developed to guarantee efficient Business Intelligence and how to automatize handling and visualization of data from different systems to assist improvement and analytics. The study was conducted in a case organization, which had a need to develop digitalized reporting procedures and ways of working. With this research we were aiming to find solutions for problematic practices and processes in continuous improvement and cost of poor-quality data integration in case organization, from management reporting perspective.

During this project, a visible and on-line data-based reporting procedure was created. The generated automatized and digitalized process benefits the BI tool, Microsoft Power BI, and it enables the obtaining of processed COPQ information out from one channel. Most importantly it enables integration between ERP data and continuous improvement data. However, there are still challenges with data quality and integration, which effects directly management reporting. The development work must continue as daily work in the organization.

The created Power BI dashboard visualized the remarkable challenge of COPQ reporting. A majority of costs were reported as code “Responsible code missing”. To be able to affect COPQ, it is essential to dig into the real root causes. This is the reason why a manual PA coding process was launched, with the root causes being reported manually to the ERP system. It reduced the PA99 coding percentage remarkably from 58 % to 16,6 % and established the major COPQ root causes. However, the manual coding process also revealed an error in the Data Warehouse logic and proved that data visualization can be a valuable tool in quality control, not just for data quality, but also from an IT quality perspective.

The research showed that even though there are progressive and effective BI tools in use, it does not remove the meaning of data quality. Even the most powerful reporting tools are useless, if the data is not of high-quality and clean. To be able guarantee data

quality and to be able to exploit data effectively, it requires the regular maintaining and cleaning of data. Data quality is primarily a business issue and it should be the responsibility of every manager. They should implement a set of procedures and a culture within the organization that promotes and sustains good-quality data. It is not just about cleaning the data, it is all about effective management, as BI must be integrated into organizational processes and it must be continuously improved. As the Gordon stated (2013, p. 96) *"there is no point in having a project to cleanse the data without putting in place the environment to maintain the data in a clean state".*

According to this research, one remarkable obstacle for data integration is that systems enable the filing of information in multiple formats. When the data is not in same format, it is quite impossible to integrate it from several systems into one reliable report. This may easily seem that there is an error in the systems, but basically it is about the change management process as people should change their ways of working and start reporting needed information properly, according to instructions and concluded procedures. Until the reporting procedure is completely implemented in the case organization and practices are established in every function, the role of the Data Engineer should be defined.

As long as the Business Intelligence process is undefined at corporation level and uniform procedures being undefined, with the process not being managed target-oriented way, then every organization is getting the information from their own sources and analyzing it for their own needs from their own perspective. Furthermore, to be able to improve the performance and gain efficient Business Intelligence, organizations need to collect the relevant data, integrate it into useful information, analyze it to gain knowledge and generate it into "intelligence" decisions and action.

9.1 Reliability and Repeatability

This research aimed to change the current ways of working and develop the procedures in case organization. The research can be seen as a collective learning process in the case organization as it produced new information about Business Intelligence and highlighted

the meaning of data quality in management reporting. It gave an insight for future development work and started a fruitful discussion. As the time was limited, only a certain level of development was achieved. The research rose up new insights for reporting and specially for COPQ root causes. However, the development work must continue as a daily work and it must be part of the continuous improvement process, which is tied to the strategy of the organization.

As the action research was targeting a specific problem and limited to internal Business Intelligence of the case organization, it is rather difficult to generalize the results. However, this research supported the previous studies as it highlighted the meaning of data quality in a data-driven decision-making process and in management reporting, as well as, the importance of Business Intelligence management.

In many cases it has been criticized that the impact of the researcher to the action research is too great. In this study, the researcher was working as the project manager and the key personnel of the organization participated in the development work and evaluation. As the researcher had a quite minor impact on the results and no chance for manipulation, the research can therefore be considered reliable.

9.2 Recommendation for Future Research

The goal of the case organization is to reduce quality costs down to a defined percentage of net sales. However, the period of this research was limited and during the timeline it was not possible to see development in this field. In future, it would be useful to study the correlation of Business Intelligence to quality cost reduction over a longer period.

As the Business Intelligence and reporting tools in the case organization provide information about past and things that already happened, it would be profitable to concentrate on analytics and predicting future incomes. Data Mining enables the predicting of future patterns, identification and classification of data, as well as, optimization of data. It helps to explore the data stored in data warehouses and finds solutions for the certain

business issues. With advanced analytics it is possible to make predictions and forecasts based on examining historical data in new ways. An organization can identify meaningful patterns and relationships in data to help predict future events and determine the best course of action (Sherman, 2014. p. 376). Therefore, studying data mining, advanced analytics and benefiting artificial Intelligence would bring more value for any future organizational decision-making process.

This research was limited only to concern continuous improvement and cost of poor-quality data integration and reporting. However, it would be interesting to study, how Business Intelligence and digitalization can be benefitted among other management reporting areas.

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