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PERCEIVED USEFULNESS OF BUSINESS INTELLIGENCE SYSTEM IN DECISION MAKING PROCESS

JYVÄSKYLÄN YLIOPISTO
TIETOJENKÄSITTELYTIETEIDEN LAITOS
2017

ABSTRACT

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Jyväskylä: University of Jyväskylä, 2017, 58 p.
Information Systems, Master's Thesis
Supervisor: Seppänen, Ville

Business intelligence systems are getting more popular in organizations. This thesis is investigating if current day users perceive usefulness of business intelligence systems in decision making. Research is clarifying the origins of decision support systems past and present state, with clarifying various systems and their goals. Technological foundations of the systems and how decision making occurs are explained. Empirical material was gathered using electronic survey distributed to various organizations. The survey consists seven background questions and 24 claims measuring eight variables. The variables included common information systems, business intelligence systems and decision making process. Results are interpreted with statistical models and data is visualized. The main contributions of this research are the following: sales is the most used business area in business intelligence systems, they are seen as useful software and decisions are driven from them. Problems in usability is the biggest restricting issue for users. The survey conducted was determined reliable and successful, but the number of respondents is limiting issue for further generalization. The results are encouraging for further studies and business intelligence systems significance in organizations is increasing.

Keywords: business intelligence, decision making, analytics, decision support system, survey, data visualization

TIIVISTELMÄ

Ahonen, Ilmari
Perceived usefulness of business intelligence system in decision making process
Jyväskylä: Jyväskylän yliopisto, 2017, 58 s.
Tietojärjestelmätiede, pro gradu -tutkielma
Ohjaaja: Seppänen, Ville

Liiketoimintatiedon järjestelmät ovat kasvattaneet suosiotaan. Tämän tutkielman tavoitteena on selvittää edesauttavatko nämä järjestelmät päätöksentekoprosessia. Tutkielmassa esitellään päätöksenteon tukijärjestelmien synty, historia ja tällaisten järjestelmien erilaiset tavoitteet. Järjestelmien teknologiset taustat ja päätöksentekoprosessi esitellään. Tutkielman aineisto on kerätty elektronisella kyselylomakkeella eri organisaatioiden työntekijöiltä. Kyselylomake koostui seitsemästä taustakysymyksestä ja 24 väittämästä mitaten kahdeksaa eri muuttujaa. Muuttujat käsittävät yleisiä tietojärjestelmiä, liiketoimintatiedon järjestelmiä sekä päätöksentekoprosessia. Aineiston data on analysoitu tilastollisilla menetelmillä ja visualisoitu. Tutkimustuloksina saatiin käyttäjien kokevan myynnin olevan tärkein liiketoiminnan ala kyseisille järjestelmille, ne koetaan hyödyllisiksi sekä auttavan päätöksentekoprosessia. Vaikean käytettävyyden koetaan olevan suurin käyttöä haittaava tekijä. Kyselytutkimus oli luotettava ja onnistunut, mutta vastaajien määrä rajoittaa tutkimustulosten yleistettävyyttä. Tulokset kuitenkin inspiroivat jatkotutkimuksiin ja liiketoimintatiedon järjestelmät kasvattavat merkitystään organisaatioissa.

Asiasanat: liiketoimintatiedon hallinta, päätöksenteko, analytiikka, päätöksenteon hallintajärjestelmä, kyselytutkimus, datan visualisointi

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1 INTRODUCTION

People are in the focus in every information system, so studying decisions made from business intelligence systems is studying people. Davenport concluded his thoughts in an interview:

> Decision-making is largely a human endeavor, so any focus on DSS and business intelligence should include a focus on how humans actually use systems to make decisions; Knowledge is both created and applied in the mind of a human knower, so attempts to manage it should deal explicitly with those humans. (Power, 2007.).

Decision support systems (DSS) focus is on improving managerial decision making. DSS has been for long time important part of the whole information systems (IS) field. Criticisms regarding how DSS field has been studied has emerged and more emphasis on professional relevance and theoretical foundation is needed. There are two promising fields: data warehousing and business intelligence. Behavioural decision theory from Herbert Simon is used in the field and this should be expanded to address more theories on this topic. IT industry is growing and academic work should be increased to expand the view from academic viewpoint. (Arnott & Pervan, 2005.).

How business intelligence systems help to make decisions? An extensive amount of citation gained article from Negash (2004) titled "Business intelligence" sheds some light on why this area has become important in IS discipline. Business intelligence systems main purposes include combining analytical tools over operational data, thus presenting complex and competitive information for the use of planners and decision makers. The main idea is to improve timeliness and quality of decisions. Decisions are based on multiple factors and to better understand e.g. trends, markets, technologies, regulatory environment and competitors' actions including their implications. These goals are met with sophisticated data warehouses integrated to web architectures allowing richer business intelligence environment. Suggestions for few further research areas are managing semi-structured data, achieving real-time business intelligence (BI) and investigating relation to business performance. (Negash, 2004.).

Wixom and Watson (2010) discuss how business intelligence can transform organizations into a new level. They argue that business intelligence is a prerequisite for competing in the markets for BI-based firms. There are several possible targets to utilize BI and they differ from each other in terms of sponsorship, required resources, processes, impact on people and vision, not to forget benefits. They discuss the relationship between BI and decision making and suggest more studies on how BI fits within the process of decision making. How information is displayed is seen as a factor affecting how user accept and use the systems, thus decision making process. The researchers emphasize the fact that decision making is well studied phenomena, but studies need to translate this knowledge into structures, processes and designs to improve business intelligence systems' effectiveness. BI systems' unstructured data formats are also worth to consider how they can be used in decision making process. (Wixom & Watson, 2010.).

IBM has studied their own business area and their 2011 report indicated that business analytics is important factor in their organization. Business analytics includes business intelligence, statistical analysis and data warehousing to name a few. According to their responders, they saw education, healthcare, aerospace/defence, computer software and life science industries to have highest impact. The report points out that analytics is not very new topic, but it is gaining momentum. (IBM, 2011.).

Five-phase model is developed to categorize how businesses use their analytics. In this model, businesses are categorized into phases and how analytical the whole company is. Analysing the company and identifying large scale of factors provide what "analytical competitors" have compared to "analytically weak". Technical capabilities do not change the company's culture, therefore emphasizing the importance of passionate top management increases the success to change into analytical competitor. This transition takes usually years and often involves change in employees, as well as executives. Successful change management in essential, when a company is going through this magnitude change. (Davenport & Harris, 2007.).

1.1 Scope and limitations

A scope of this thesis is to investigate information transformation and connection between business intelligence system and a decision. Figure 1 explains the scope: information is generated, user processes it and makes a decision. The proposed benefits are involved in the user's decision making process, which are measured in this thesis. From this figure, the scope is the arrow "user", because their perceived usefulness in this process is the main research question.

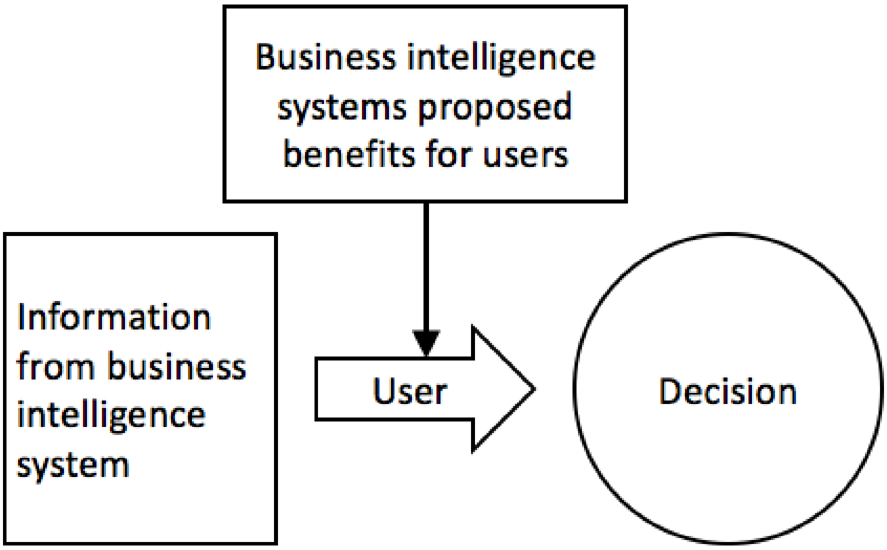

Figure 1 - The scope

This scope has formed from the literature and main topics are decision support system, executive information system, business intelligence, analytics and organizational decision making. As seen from Arnott and Pervan's (2005) article, decision support systems field is diverse. They study for example intelligent decision support systems and negotiation support systems, but in this thesis, those will not be present. The reason is lack of literature, thus unsuitability for this research. The second chapter will introduce the supporting background for the empirical study.

Some limitations are present: lack of respondents and insufficient amount of theoretical foundations. Lack of respondents is presumably because of difficulty to reach the right people, for Finnish speaking respondents usage of English and the diversity of the area causing confusion if the system in use is actually a business intelligence system. Insufficient amount of theoretical foundations caused issues resulting confusion of terms and conflicting literature. Development speed of technologies and tools might produce conflicts between the technologies presented and what are used in latest software. These issues are important to notice, but they also justify this thesis to be made. One aim for this research is to rearrange the literature to provide sustainable survey example for future studies.

1.2 Objective of the thesis and research questions

This thesis is studying how business intelligence systems are used in organizations supporting decision-making process. Literature review is conducted with how current business intelligence field has emerged and what technologies are involved. Decision-making process in organizations is discussed with the notation how business intelligence systems are designed to support decision-making process. A survey was conducted reaching professionals using this kind of systems and results were analyzed using statistical models. The following research questions are formed to produce answers how users perceive the systems.

RESEARCH QUESTIONS

- How businesses use their business intelligence systems?
- Do users recognize the usefulness of business intelligence system?
- Do organizations use their business intelligence system in decision making?

Sub-questions:

- What business area is the most used in business intelligence system?
- Do companies focus more on information content quality than information access quality?

This thesis is structured as follows: Chapter two will present the literature review considering decision support systems, technologies enabling the systems, organizational decision making process, analytical organization and a conclusion. Chapter three will present the survey and its justification. Chapter four will include results of the data gathered from the survey in two parts: statistical analysis and data visualizations. Chapter five is a discussion of the results and answers to the research questions. The last chapter six will present the conclusion of this research with propositions of further studies. Reference list is before the appendix, which includes the survey used for data acquisition.

ABBREVIATIONS

DSS	Decision support system
EIS	Executive information system
KM	Knowledge management
BI	Business intelligence
BIS	Business intelligence system
OLAP	Online analytical processing
ETL	Extract-transform-load
DM	Data Mart
DW	Data Warehouse
KPI	Key performance indicator

2 BUSINESS INTELLIGENCE AND DECISION MAKING

In this chapter I will elaborate the field of business intelligence, its past and present state. Understanding how current business intelligence systems are made today, the first look is to how systems have evolved what they are at the moment. This chapter will be constructed in chronological order dating back to the 1960's and then clarifying the variety of what this kind of systems are called. At the end of the chapter I will go through data storage and retrieval technologies, decision making process in organizational perspective and what analytical organization means. This chapter will elaborate the field of business intelligence and provide a clear understanding how the survey was constructed.

Decision support systems (DSS) is an umbrella term for many kinds of systems. One definition for this is: "Decision support systems (DSS) are computer technology solutions that can be used to support complex decision making and problem solving." (Shim et al., 2002, 1.).

Two main research areas have evolved DSS; theoretical studies of decision making in organizations (originally from Simon, 1960) and technical work (originally from Keen & Morton, 1978). During three decades, DSS has seen both narrow and wide definitions (Shim et al., 2002). Decision making can be measured in two ways: efficiency in a manager's decision making process or effectiveness of that decision. Research has focused on these two factors and how these relate to decision support technology (Pearson & Shim, 1995). Arnott & Pervan (2005) in their critical analysis of DSS research point out few distinctive features that this field has had from 1990 to 2003: steady falling of publications, data warehousing to be the latest topic, empirical research has been overwhelming positivist and good balance among development, technology, process and outcomes.

The first systems dedicated to support decision making emerged in the late 1960's (Watson, 2009), executive information support systems in the late 1970's (Rockart & Treacy, 1981), business intelligence term was created in 1989 by Howard Dresner (Watson, 2009) and knowledge management systems in the early 1990's (Alavi & Leidner, 2001). All of these have similar goals: support organization to perform better, aid decisions to be made and provide competitive advantage by improving information usage. The following chapters will elaborate more the specifics of each system. At this point I want to draw attention to the whole field of DSS: it is not homogenous field, there are many approaches to DSS and popularity in research or practise. Differences include supporting philosophy, scale of the system, investment level and potential impact on organization level (Arnott & Pervan, 2005).

2.1 Decision support systems

The first computer applications in the 1960s were developed for scientific purposes and transaction processing. In 1967 Michael Scott Morton built, implemented and tested a support planning system in his doctoral dissertation research. The name for that system was management decision system. (Watson, 2009.). Figure 2 presents a taxonomy, which has two significant aspects: the use of DSS as an overall term to address many decision support applications, and the notation of how application can be data- or model-intensive (Alter, 1977).

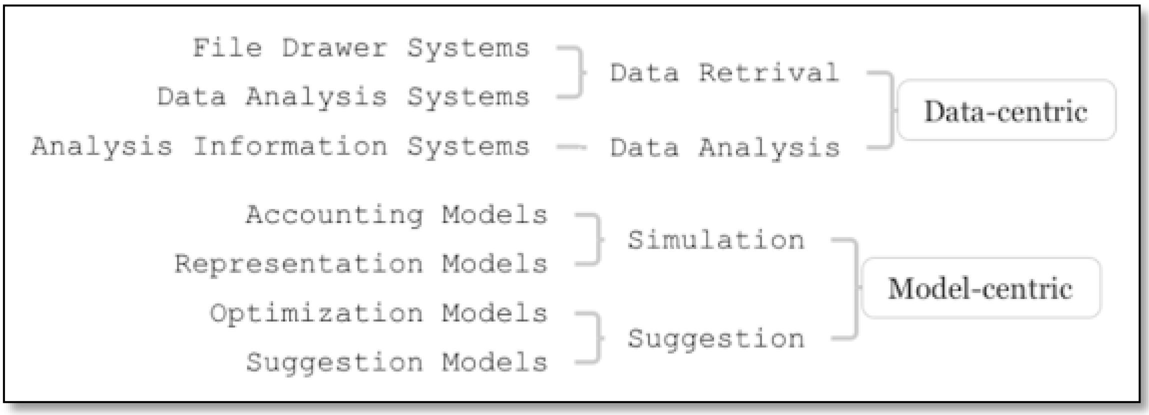

Figure 2 - DSS Taxonomy, adapted from Alter (1977, 42)

Shim et al. (2002) and Arnott and Pervan (2005) notices Gorry and Scott Morton (1971), who made a clear original concept of DSS. Gorry and Scott Morton combined the work of Anthony (1965) and Simon (1960), where Anthony categorises management activity and Simon describes different decision types. A framework from Gorry and Scott Morton included intelligence, design and choice descriptions how decision process works. Intelligence contains search of a problem; design is about developing alternatives and choice is analysing and choosing the best solution. Gorry and Scott Morton claimed that characteristics of information needs and models differ in DSS and for example relational databases and flexible query languages are needed. (Shim et al., 2002.).

Some theoretical frameworks have been done and one specific older framework was developed for knowledge-orientated decision support systems. This included four aspects or components: 1. A language system that agrees the messages the decision support system accepts; 2. A presentation system, which the decision support system displays; 3. A knowledge system about the knowledge decision support system includes and 4. A problem-processing system for recognition and solving the problems. Importance of artificial intelligence in decision support systems development was recognized. (Bonczek, Holsapple & Whinston, 1981.).

The effectiveness of DSS is important factor to cover. In a study, which observed students' fictional business game, half of the students were using a DSS. Almost every measurement tool the DSS using half won the game with significant margin. Only average time spent in decision making was higher, which can be explained with learning the system. (Sharda, Barr & Mcdonnell, 1988.).

Decision support system field has undergone changes over the years and it will continue to evolve due to technological improvements and users changing behaviour patterns. Even though the name of the system has been changing, the purpose and fundamentals of DSS concept has not. Artificial intelligence is increasing importance over various fields and as technology develops it can contribute to decision support systems. As Sharda et al. (1988) recognized the usefulness of DSS, learning the system is essential for users to utilize the benefits for themselves and for their organizations.

2.2 Executive information systems

The name "Executive information system" implies that the system is meant to be used for high level strategic decision. Rockart and Treacy (1981) used the term "executive information support" (EIS) and predicted its rapid growth in the 1980's. Rockart and Treacy concluded six characteristics of EIS: (1) Senior line managers desire to retrieve and analyze information to improve performance. (2) Existing concepts are incomplete. (3) A few organizations have made meaningful progress in this area for several years. (4) This emerging field can be meaningful for managers. (5) EISs are a new way to use computer and it requires new managerial perspective, therefore past techniques are inadequate. (6) These systems have significant implications for executives.

Arising demand for systems designed for executives came from decision support systems, which were designed and used mainly by lower and middle management. Executive information system is defined as a computerized system providing internal and external information, which is relevant in critical success factors for executives. Characteristics of this system are displaying information graphically, it is used directly by executives, broad range of data, providing trend analysis, exception reporting, and online status check. Distinction between executive information system (EIS) and executive support system (ESS) is that the later one provides more capabilities, for example communication, data analysis and organization tools (calendar/rolodex). These two names are used as synonyms of each other. (Watson, Rainer & Koh, 1991.).

Shim et al. (2002) argue that executive information systems came to extend DSS field from personal or small group use to bigger corporate level. Interestingly Arnott and Pervan (2005) in their literature study combine EIS and BI into single category, which can be partly explained by the publication year.

Executive information systems can be classified into two perspectives: EIS for collaboration support and EIS for decision support. This was first introduced by Turban, McLean and Wetherbe (1996). Collaboration is described as communication and coordination, which are supported by this system. Decision support is described as giving information for planning and controlling. This research points out that EISs are no longer exclusive for larger firms, but can be adopted to smaller as well. Environmental uncertainty is found to be adaption process motivator and especially for EIS for decision support, information system support was critical enabler. Top management support was found to be critical factor for adaption. (Rai & Bajwa, 1997.).

Executive information systems became to adjust the scale and focus of decision support systems, with their distinctive features like communication and calendar applications. Still the basic aim to support executives to make better decisions lasted, so to conclude why executive information systems were made in the first place was the need to expand the field of DSS to cover executive level, give more information to strategic decision making and to support executives needs overall.

2.3 Knowledge management systems

Knowledge management systems are made for organizational knowledge management mainly with IT technology. Their main duties are knowledge creation, storage and retrieval, transfer, and application (Alavi & Leidner, 2001). Ways to accomplish these are creating virtual teams, accessing information from older projects, analysing customer needs and accessing transaction data (Alavi & Leidner, 2001 citing KPMG, 1998). Alavi and Leidner highlight the difficulty to manage knowledge, with the reasons varying from technological to classifying the knowledge to be managed. They argue that most DSSs are focusing on explicit knowledge and knowledge management systems should be expanding this field. Nemati, Steiger, Iyer and Herschel (2002) explain that KM is capturing tacit knowledge and transforming it to explicit knowledge (more in chapter 2.7).

Arnott and Pervan (2005) use term knowledge management-based DSS, which implies that knowledge management systems are not only DSSs, but rather large systems including same capabilities as DSS. This brings an interesting aspect for knowledge management systems: they are mostly seen as partly decision support systems with increased attention to tacit knowledge. Several articles (see Herschel & Jones, 2005; Cody et al., 2002; Cheng, Lu & Sheu, 2009) are discussing how KM and BI should be or are integrated. An article from Nemati et al. (2002) argue the importance of knowledge warehouse (KW) architecture. They focus on creating a warehouse for knowledge to be distributed across the whole organization, which they call the new direction of DSS.

Herschel and Jones (2005) argue in their article how knowledge management (KM) systems and business intelligence systems should be seen as integrated systems where BI is a subset of KM. The study included literature from 1986 to 2004 and it concluded how KM includes both tacit and explicit knowledge, whereas BI includes only explicit. The both systems still promote learning and decision making, but the writers argue that KM can influence the nature of BI. Knowledge management is described as "systematic process of finding, selecting, organizing, distilling and presenting information in a way that improves an employee's comprehension" (Herschel & Jones, 2005, 45).

Knowledge management and business intelligence systems was predicted to be integrated into one, called BIKM system which would combine all of the features (e.g. text mining) and provide seamless functionalities with various data sources and sophisticated data warehouse technologies. Knowledge management systems would provide valuable unstructured data to the system, which would allow for example trend and irregularity recognition. (Cody, Kreulen, Krishna & Spangler, 2002.).

Knowledge management systems functionalities for example text processing and storing data are recently moved into BI systems and some original functionalities like virtual teams are moved to other systems. KM systems aim to transform tacit knowledge into explicit will remain important, even though specialized systems have become less important. Data warehouse is important feature of BI, as it will be explained. This implies the knowledge management systems legacy to business intelligence systems.

2.4 Business intelligence systems

One definition for business intelligence (BI) is "a broad category of technologies, applications, and processes for gathering, storing, accessing, and analyzing data to help its users make better decisions." (Wixom & Watson, 2010, 14).

Negash (2004, 178) defines business intelligence as follows: "BI systems combine data gathering, data storage, and knowledge management with analytical tools to present complex internal and competitive information to planners and decision makers." Business intelligence systems consists of multiple parts from various fields, which makes them complex and meaningful for all around the organization.

Business intelligence changed the emphasis or direction of executive information systems by focusing on the whole organization-wide reporting systems. At the late 1990's there were no clear evidence of organization-wide systems success. Dashboards and web-interfaces changed the look of the systems. Business intelligence has its origins in industry, which makes the definition rather poor and adjustable from vendor to vendor. BI is both model-oriented and data-oriented, as taxonomy of decision support system presented in Figure 2, and has a contemporary nature with executive information system. (Arnott & Pervan, 2005.).

Herschel and Jones (2005) distinct business intelligence systems from management support systems from a need of a system which is active, model-based and future ready. It would discover and explain hidden, relevant and decision helping data. One important aspect, what Herschel and Jones (2005) focus on is how BI should be developed to include important knowledge, especially tacit knowledge for ultimate benefit for an organization. They would like to see integration between BI and KM, because BI's capabilities can be expanded. This integration has been happening, as explained in the previous chapters. These two systems are likely to be existing simultaneously for a while before they evolve to new functionalities and researchers define new terms.

Business intelligence systems to utilize their full potential to provide rich and informative data, the system must have broad set of data to work on. Important factors include reliable knowledge from competitors, customers, economic environment, internal operation and business partners. One specialized field of business intelligence is called competitive intelligence, which focused purely on external data from environment. (Ranjan, 2009.).

Seufert and Schiefer (2005) propose a new architecture for business intelligence systems reducing action time and connecting processes into decision making. They argue that business intelligence and data warehouses are middleware applications and the role should be increased in order to increase the value of the systems. Seufert and Schiefer (2005) argue that BI systems are targeted for process-oriented organizations, which is supported by Bucher et al. (2009). Bucher et al. uses a term process-centric business intelligence, which is described as systematic transformation of data into analytical information embedded into an operational process. Therefore, this is used to support decision-making in process execution context.

Key performance indicators (KPI) are one way to use business intelligence systems data and analytical capabilities to inform users. KPIs can be customized for customers' needs and once a threshold values are met, the system will alert users to take action (Bucher et al., 2009; Seufert & Schiefer, 2005). These indicators require real time data to operate and managers must be prepared to take actions quickly.

Business intelligence has clear roots from the three aforementioned systems, but the evolvement has been organic to meet changing demands. Terminology of these decision support systems has changed from various reasons in academic field, as well in industry, but the goals have stayed much alike.

2.5 Data storage and query technologies

Independent data marts have origins in early DSS where data was more application dependable. They often had inconsistent structure, dimensions and measures, which made distributed queries difficult to achieve. Their maintaining was costly and time consuming, but this changed in the late 1980's, when data warehouses became to support organization-wide data repositories. (Wixom & Watson, 2010.).

Chaudhuri and Dayal (1997, 1) describe data warehousing as "a collection of decision support technologies, aimed at enabling the knowledge worker (executive, manager, analyst) to make better and faster decisions". Data warehouses are designed to be used in decision making and they support on-line analytical processing (OLAP), which differentiates them from more common databases. Data warehouses consists of historical, summarized and merged data, which expands their size over databases. Querying data from warehouses need to happen ad hoc and instantaneously. OLAP technology is developed for multidimensional warehouses and common query language SQL has evolved to support OLAP style multidimensional queries. (Chaudhuri & Dayal, 1997.).

OLAP data is typically presented in multidimensional data cubes, where raw data is already processed for faster queries. This precomputing results to summary tables and indices, which both consume space (Gupta, Harinarayan, Rajaraman & Ullman, 1997). OLAP data is typically used for analysis, reporting, modeling and planning to improve business operations and the processed data is then forwarded to other tools, such as visualization or decision support (Ranjan, 2009). OLAP cubes consists of multiple spreadsheets (usually up to 7), which are individually similar to spreadsheets used in Microsoft Excel. These cubes are difficult to operate, therefore they are built by experts and sent to users. (Davenport & Harris, 2007.).

Data mining is artificial intelligence software, which can be categorized into two distinctive categories: verification- and discovery-driven. Verification-driven data mining searches data with predetermined patterns and tries to find a match. Discovery-driven is mining the data without any patterns, but tries to find meaningful correlations. (Nemati et al., 2002.). Verification-driven approach can be used for example in financial situations, where stock price is followed and when predetermined key levels are met, an action is taken. Discovery-driven mining technology could be used to find the most promising customers, whom to increase marketing actions. Fayyad, Piatetsky-Shapiro and Smyth (1996) describe the overview of a data mining process: selection, preprocessing, transformation, data mining and interpretation/evaluation steps. This results into new knowledge generated from a set of data.

Data warehouses are seen as a layer between transactional applications and decision support systems, which requires the technology to be able to transform data into consistent and integrated input for decision support systems. A critical function in a data warehouse system is extracting data from operational systems, transforming it into correct format and then loading it (or Extract-Transform-Load (ETL)). This is highly resource intensive and time consuming. (Seufert & Schiefer, 2005.).

Data can be structured or unstructured (some use term semi-structured) or a collection of both. Structured data can be for example transaction data, delivery amounts or various data from enterprise resource planning system (ERP). These are easier to use but there is massive amount of data.

Unstructured data can be for example e-mails, images, memos, reports, web pages or phone conversations. These are harder to use and store, but considered more valuable. The source of the data can be either internal or external, even both e.g. a phone conversation. (Negash, 2004.).

Data warehouses were seen to play important role in decision support systems, which has come into reality. Information intensive society provides all the data, but the more important issue is to know what to select and how to use it. Big data is an important topic in data warehouses, where new technologies are needed to keep up with the increasing data. Cloud computing offers flexible data storage and consumption technics, where organizations do not need to build their own infrastructure. Decreasing price of storage enables companies to gather more data, thus increasing the accuracy and richness of data to make better decisions.

2.6 Decision making process in organization

Knowledge management researchers widely accept that organization has both tacit and explicit knowledge. The both types are involved in decision making process, but with different intensity. (Nicolas, 2004.).

> Tacit knowledge – practical, action-oriented knowledge or "know-how" based on practice, acquired by personal experience, seldom expressed openly, often resembles intuition. Explicit knowledge – academic knowledge, or "know-what" that is described in formal language, print or electronic media, often based on established work processes, use people-to-documents approach. (Smith, 2001, 314.).

Nicolas (2004) combines two theories from Simon (1977) and Cohen, March and Olsen (1972) and theorizes the basics of decision making. Cohen et al. (1972) argues that decision making process might not be rational and the decisions are made with incomplete or imperfect information. Cohen et al. (1972) defines this kind of process: At first the goal is to construct and understand the issue; secondly the conception phase where solutions are considered; and at last phase where the best solution is chosen. Also, Nicolas (2004) recognized this three-step process, but added how tacit and explicit knowledge work with these:

1. The intelligence phase
    a. Explicit knowledge supports the argumentation of the definition but tacit knowledge allows to understand the elements defining the complex situation (Simon, 1987).
2. The conception phase
    a. Both tacit and explicit knowledge are used for the same interest and frequency (Nicolas, 2004).
3. The selection phase
    a. People argue their choices using explicit knowledge, but tacit knowledge has great impact how they come up with the

selection (Nicolas, 2004). Intuition and feelings are used in argumentation, which are tacit knowledges (Spender, 2003).

Spender (2003) argues four principles: uncertainty resolution, complexity reduction, emotional aspect and emotions dealing in organization are the most important issues managers face. The two first principles are relevant for this research, because they can be affected with information systems, but the two later ones have an impact as well. People build and use these information systems and emotional aspect must be involved somehow in decisions. Although in this research will not be discussing emotions in decision making, but it is reasonable to understand this issue.

It is rather important to notice which knowledge, tacit or explicit, is more valuable. Alavi and Leidner (2001) discuss how majority of knowledge management studies imply that tacit knowledge is more valuable, but for example Bohn (1998) sees explicit knowledge to be more valuable. This viewpoint has been influenced with technological capabilities to gather this kind of knowledge easier. Sharing knowledge between two individuals is often tacit and explicit. For knowledge to be shared efficiently, their knowledge space must overlap in some degree. Decision makers to make correct decisions the both kind of knowledge should be used, but explicit knowledge is more justified and legitimized. This action compromises the decision to be made with smaller amount of information, thus lowering performance. (Alavi & Leidner, 2001.).

Utilizing both tacit and explicit knowledge ensures the best decisions to be made, which is the aim of every decision support system. Tacit knowledge is harder to write down but modern data mining technics are trying to compensate this issue with their discovery functions. Decisions must be well justified and the results analyzed before an action is taken. Information systems are excellent tool for complex chains and predictive modelling.

2.7 Business intelligence systems benefits

Business value of IT systems is studied extensively (see e.g. Dehning & Richardson, 2002; Bharadwaj, 2000), but developing a model for BI systems value is less studied. Organizations current systems (e.g. ERP) produce massive amounts of data daily, but that data is not fully exploited. Business value can be measured in business process performance or organizational performance. Business process performance includes processes, which are affected by BI systems and result in for example cost reductions and/or productivity increases. Organizational performance gains can be measured for example with return-of-invest –figure or revenue growth. (Elbashir, Collier & Davern, 2008.).

Major issue when discussing benefits is predictive analysis. Business intelligence technologies one important issue is to collect, use and predict future actions based on sophisticated algorithms and analysis. Reporting what has happened is significantly less important than having a model what will happen. (Watson & Wixom, 2007.).

As seen in Figure 3, many benefits are hard to measure and even harder to trace back to the origin. Elbashir et al. (2008) used perception-based measurement method, because nature of BI benefits are intangible or qualitative and therefore not objective measures. This issue was carried along the survey.

Figure 3 - Spectrum of BI benefits. Adapted from Watson and Wixom (2007, 97)

Information is regarded as second most important resource after people, which shows the significance of precise data. Reacting to financial changes or supply chain operations is enabled by precise and timely data. Some practical examples of BI systems benefits: Identifying the most profitable customers and the reasons for that, have a clear picture how customers behave in e-commerce site, discover frauds, and detect customers' reasons for churn. (Ranjan, 2009.).

2.8 An analytical organization

Organizations face many kind of threats and competitive advantage is difficult to achieve. Information systems have provided a leverage in many kinds of companies in the past 21st century. Transforming into an analytical company from more traditional "let's see how it goes" company is a serious work. Davenport and Harris (2007) focus on introducing five-phase model in their book how a company can become analytical competitor. Industry or the size of the company is not relevant how analytical it can be, as Davenport and Harris provide wide range of examples: baseball team (Oakland A's), video renting service (Netflix), casino group (Harrah's), credit company (Capital One) or retail chain (Wal-Mart). These companies have few distinctive qualities: top management's passionate commitment, company-wide analytical mind set, correct technologies and clear set of aims. (Davenport & Harris, 2007.).

Wixom and Watson (2010) identify three BI targets, where the first one is using only a single or few BI applications and mostly for one department only with the help of a data mart. The second target is an infrastructure supporting

BI needs, building a data warehouse and BI impacts the whole organization. Third target is where BI is responsible of the whole organization's change how it performs in the marketplace. BI enables new business models and strategies, thus transforming and benefiting the whole organization.

2.9 Conclusion of literature review

Business intelligence systems are diverse and contains a lot of models, technologies and terms. In the Figure 4, the aim is to give clear idea how these systems are built and how data flows through. The figure is built mainly to support this literature review and it does not contain any non-relevant parts which would be usable in another context.

Allocation between structured and unstructured data is done with presumptions how the data is usually seen. As mentioned, in most cases data uploaded to data warehouse is mixture of both kinds of data. In data warehouse OLAP and data mining actions are made, before forwarded to BI system.

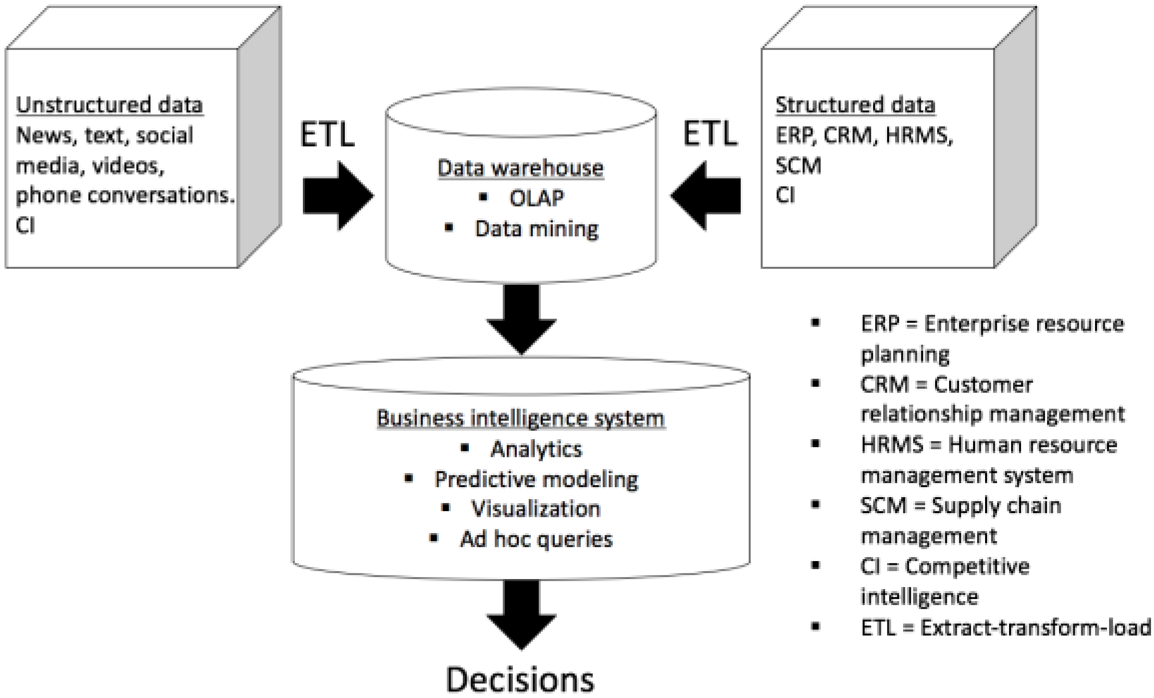

Figure 4 - Information flow through business intelligence system. Adapted from Negash (2004); Davenport (2006); Watson and Wixom (2007); Baars and Kemper (2008)

Figure 4 presents a simplified structure of a system, where external and internal data is send to a data warehouse. The data warehouse can consist multiple databases and multiple technologies. Big data technologies are often present, but not all data is structured in the same way and cloud technologies enable flexible access to data. Business intelligence system (or systems) is the main user interface, where the data is explored and information is generated. Users are the actors between the system and decisions, therefore functionalities of the system determine large part of the decisions quality.

Business intelligence systems are clearly seen as beneficial and even crucial component of competitive company, but to answer the research questions a survey has been conducted. In the next chapter structure of the survey and justifications are explained. As mentioned in the beginning of the first chapter, studying decisions is studying people.

3 RESEARCH METHODOLOGY

Literature review brought up research gaps and the next step is to conduct an empirical study aim to address the research questions. A survey was selected to be suitable for testing eight variables concluded from literature. Quantitative method provides large set of data and workable depth of the answers. Majority of the questions are simple opinion and/or perceived view –based assumptions, which participants have. Qualitative study was considered to be less generalized for more common opinion, although interviews would have resulted into deeper understanding of the researched issues. The most suitable research method for this study is quantitative method. In this chapter will be an explanation how the survey was designed and what does it include. See appendix 1 for full survey.

Figure 5 is an explanation how the survey has constructed and from which scientific area the variables are brought. As seen from chapter 2, the field of business intelligence is part of information systems science discipline and has elements from organizational theories, more preciously decision theories. Decision theories subsection has claims about decision making process and whether users use actively business intelligence systems as decision making tool. Information systems science subsection provided common theories from general information systems usefulness and ease of use. These factors are present in every system, therefore meaningful to address here as well. Business intelligence literature brought issues relating to data quality: accuracy and relevancy. These make the system trustworthy and imply the main reasons why these systems have been implemented. Vitality and insights are possible additional features, which users might experience, thus increasing their acceptance towards the system in decision making. Background questions were designed to give more descriptive explanations of the participants' context as business intelligence system user. Comparison, whether content quality or access quality is more important, was done using Likert –scale.

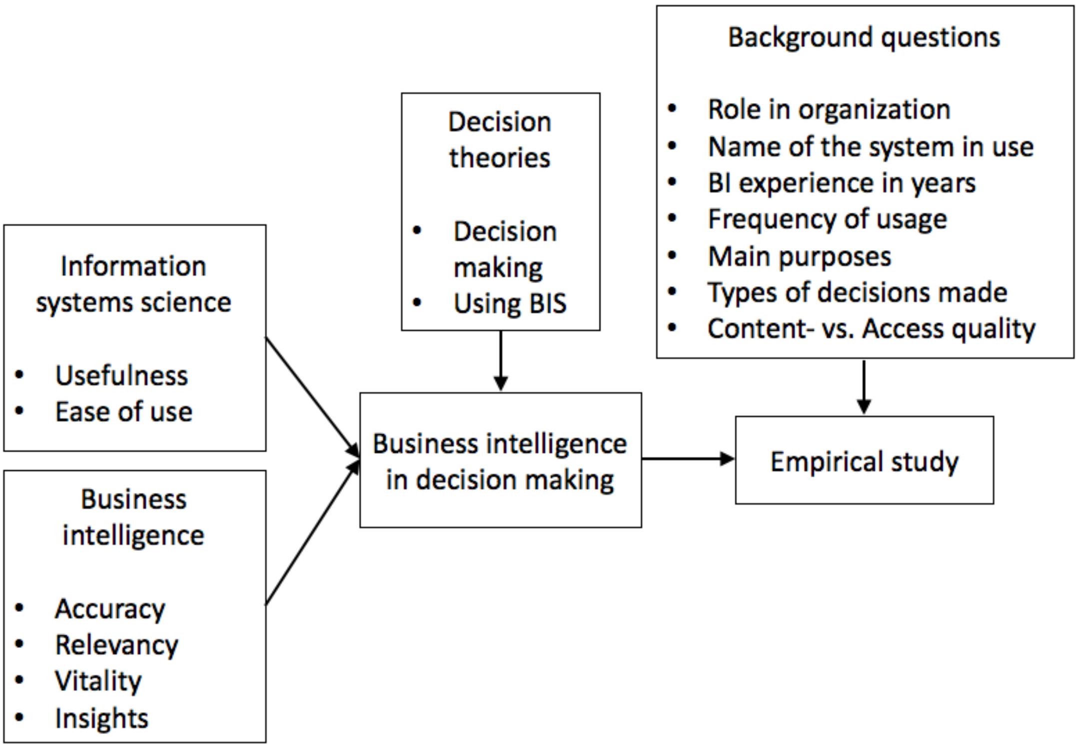

Figure 5 - Survey's context where the variables are concluded

3.1 Survey's structure

The survey was developed by using three parts: what is decision making, how information systems generally work and what kind of aspects business intelligence system offers. The survey included eight outcome variables, which all are briefly introduced and explained how the measures are involved in this survey.

Usefulness
When using a certain business intelligence system, decision must be driven from something and the usefulness of this system is one key element how users perceive the need to use it. This value has both tacit and explicit knowledge elements, because raw data itself is explicit, but when generating correlations behind it, tacit knowledge increases. Users need to see more value towards the system than effort to use it.

Ease of use
Systems to fully benefit organizations, usefulness is as important as ease of use. When a system is relatively quick to learn, users are more willing to utilize its full potential. Ease of use increases users' willingness to use the system.

Accuracy
Explicit knowledge must be right and precise to make well justified decisions based on it. Data needs to be trustworthy and not to contain too many errors.

Trust towards the system can be decreased, if accuracy of the data is compromised. Intuition can be increased if data is incomplete or there is a doubt of errors.

Relevancy

Even if the data from the system is accurate, it needs to be relevant what the user was searching. Relevant data increases the explicit knowledge towards a certain decision, therefore this factor is highly relevant to measure.

Vitality

Vitality is an extreme measure from usefulness. This issue is important, because the survey measured usefulness at first, but knowledge if usefulness can evolve into vitality is interesting. Vitality of BIS for organization means BIS acts as a huge part of every day, but it doesn't still mean the organization fully benefits from it.

Insights

Business intelligence system is able to discover new insights from the data and therefore increase knowledge on its own. This requires advanced technology and fully utilizing it, therefore this variable indicates analytical organization.

Decision making

Business intelligence systems origins are in decision support systems; therefore, it is important to measure if users are seeing them as such. Participants in this survey were from diverse positions in organizations and decision making should be a part of every user. The scale of the decision was not considered to be a relevant factor, which was mentioned in the intro of the survey.

Using business intelligence system

This variable measures if users are seeing business intelligence system to be part of their decision making process. This indicates high trust for the system and using extensive amount of information gathered from the system. The previous seven variables are combined to one, with the aim to find users consideration if they actually use the system to make decisions.

In table 1 are displayed the outcome variables, items used and how the variables have been developed. The background literatures are not fully listed, but the main influencers are presented.

Table 1 – The claims of the survey

Outcome variable	Items used			Variables adapted from
Usefulness (UFN)	UFN1 I think that the business intelligence system I use is useful.	UFN2 I am sure that the business intelligence system I use gives me valuable information.	UFN3 I consider that the business intelligence system I use is beneficial.	(Davis, 1989; Moore & Benbasat, 1991)
Ease of use (EOU)	EOU1 I get the information I need easily from our system.	EOU2 Information I am looking for can be found easily.	EOU3 I have always found the information I have been looking for.	(Davis, 1989; Moore & Benbasat, 1991; Wang & Strong, 1996; Venkatesh et al., 2003)
Accuracy (AC)	AC1 I believe that I get exact information from the system.	AC2 I trust that business intelligence system gives me accurate information.	AC3 Our business intelligence system gives me precise information.	(Wang & Strong, 1996; Wixom & Todd, 2005)
Relevancy (RE)	RE1 I believe I get relevant information from the system.	RE2 Information I get is highly related what I was looking for.	RE3 Business intelligence system offers me pertinent information.	(Wang & Strong, 1996; Wixom & Todd, 2005)
Vitality (VI)	VI1 Business intelligence system is vital for my organization.	VI2 Our performance would hurt without business intelligence system.	VI3 Business intelligence system is essential for my organization.	(Venkatesh et al., 2003; Sahay & Ranjan, 2008)
Insights (IN)	IN1 Business intelligence system has brought new information, which I haven't been looking for previously.	IN2 I have found new insights while using business intelligence system.	IN3 I understand deeper associations after using business intelligence system.	(Seufert & Schiefer, 2005; Herschel & Jones, 2005)
Decision making (DM)	DM1 I consider that the business intelligence system I use helps my decision making.	DM2 Decisions I make are more confident because of business intelligence system.	DM3 Choices I make are supported greatly by business intelligence system.	(Venkatesh, Morris, Davis, & Davis, 2003; Tvrdikova, 2007; Sahay & Ranjan, 2008)
Using BIS (UB)	UB1 I use frequently business intelligence system when	UB2 Business intelligence system allows me to do better decisions.	UB3 Decision I have made with the help of business intelligence system has been better than	(Venkatesh et al., 2003)

	deciding actions.	without it.

3.2 Quantitative method

3.2.1 Distribution method

The survey was distributed online through Google Forms. The link to the survey was distributed using emails and LinkedIn groups. One consultant company in Jyväskylä provided their help by sharing their customers email addresses, which has an effect why QlikView –BI system is overrepresented in the answers. TDWI Finland, which is a worldwide organization focused on transforming data with intelligence (TDWI), spread the survey within their professionals. Professional networks in LinkedIn was used by sharing the survey in business intelligence –themed groups. Few tens of emails were sent directly to companies and a couple of positive answers were got. Overall direct contacts are estimated to be approximately 600 and indirect 200 000.

3.2.2 Responses

38 responses were gathered, which means around 6% response rate from direct contacts. One sample was deleted, with only three questions answered. This results to 37 useful responses, which is less than expected one hundred. Validity of this scientific study reduces because of the lack of responses. Small amount of responses narrows the possibility to generalize the findings to a larger population. This study remains to be an explanation how these respondents perceive decision making, but with larger amount some generalizations could have been made.

The reasons for small amount of responses are seen to be difficulty to reach suitable people, small number of cooperating companies and difficulty to reach out people from massive social media groups. Direct contacting of presumably suitable people was hard to achieve, mostly because business intelligence systems are used in every industry and therefore contacting various companies would have resulted small amount of responses compared the time used. Contacting consultant companies providing business intelligence software resulted with one positive cooperation, but several other requests were made. LinkedIn groups lack of responses resulted from frequent posts, hence the active time for each post to be on top was short.

4 RESULTS

The survey was online 6 weeks, in which time direct contacts were made three times and indirect three to five times. In this chapter the results of the survey are displayed and visualized, as well as statistical calculations performed. Software used were IBM SPSS, Microsoft Excel and Tableau Desktop.

Statistical analysis includes determining if the variables of the survey are reliable, how independent variables affect dependent variables and what are their correlation with each other. Data visualizations are presenting the background questions with various graphs used to present data. The graphs are explained and then the results are discussed.

4.1 Statistical analysis

Table 2 represents each variable average value from the three measurement units.

Table 2 - Average value of each variable

Variable	Overall average
Usefulness	4,2162
Ease of use	3,4775
Accuracy	3,8468
Relevancy	3,9992
Vitality	4,0093
Insights	3,8103
Decision making	3,9329
Using BIS	3,9897
Total average	3,9102

These average values are reasonably consistent, with exception of usefulness (~4,2) and ease of use (~3,5). These both variables are part of basic information system and important to information system adaption. Usefulness has the highest overall average, which implies the users see the systems possible benefits. Ease of use on the contrary implies the difficulty to utilize the systems full benefits for users' service. This is clearly a problematic issue for business intelligence system manufacturers, as it seems to be that users have willingness to use the systems but lack of skills to utilize the full potential. Organizations should increase training of the system for employees for achieving higher results as users are seeing the usefulness of the system.

Figure 6 displays the variables spread across the possible range of 1-5. Box-and-whiskers plot displays the variables each value on given scale, draws a box between calculated values using median ± upper/lower half and whiskers for each value. Whiskers are made using Tukey's 1,5 times IQR method, meaning the lower and upper whiskers are calculated with 25% and 75% times 1,5 and drawn to closest value. Average values are added with a line inside of the box.

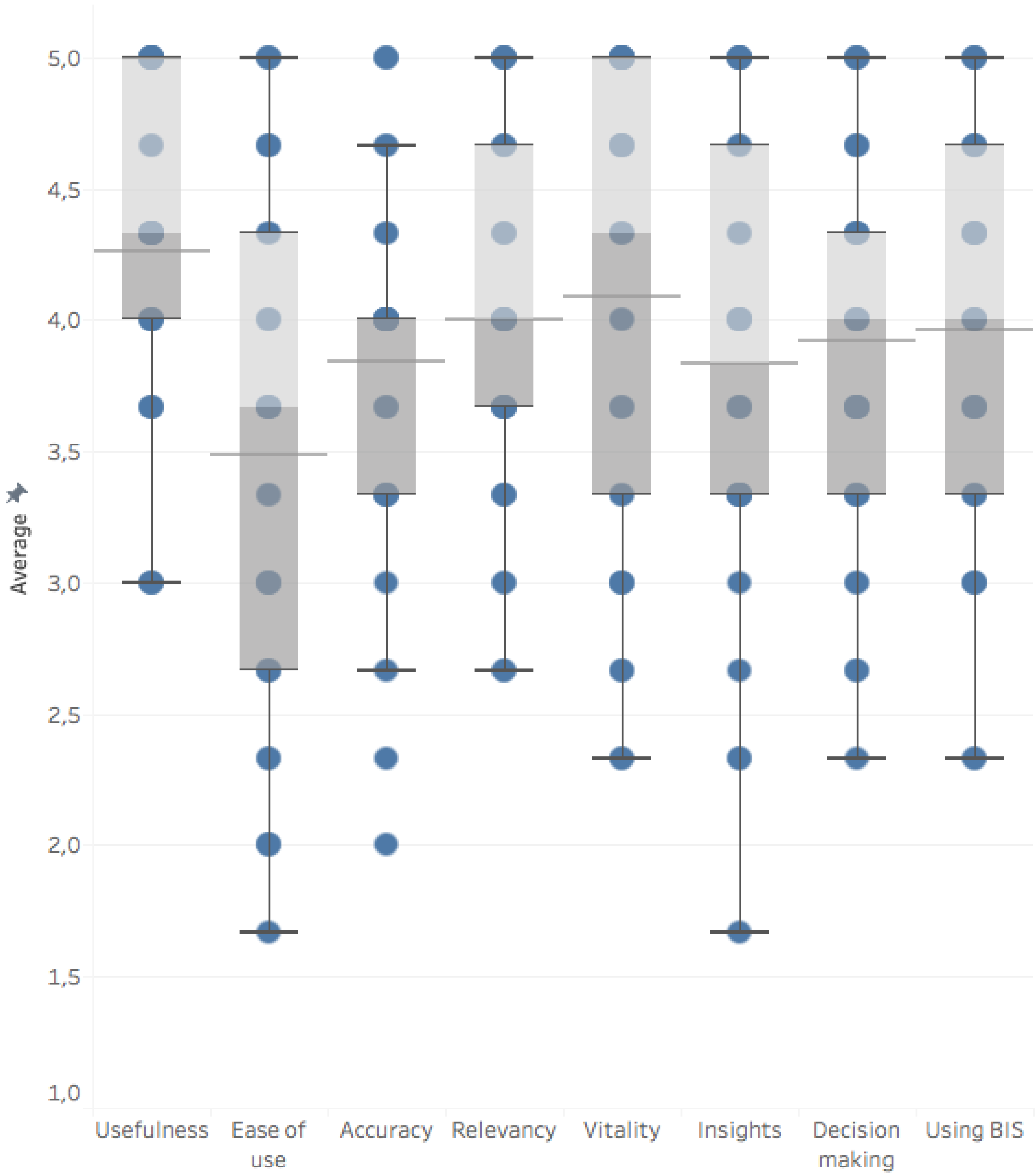

Figure 6 - Box-and-whiskers plot of average values for each variable

Box-and-whiskers plot is showing how the values are spread and mostly there are no dramatic differences. The highest on average, usefulness, draws a box from 4 to 5, implying high average with lowest value of 3. Accuracy is very consistent and the box does not include upper half and has narrow whiskers. This implies the values are close to each other with only few high/low values. Insights and Ease of use –variables are dividing the respondents with larger variance between values and both resulting to as low as 1,667 lower whiskers. Data is fairly consistent and there are only few exceptional values.

4.1.1 Cronbach's alpha

Cronbach's alpha is used to measure reliability of variables. In the survey, each variable was measured three times with slightly different question to increase reliability. Calculating alpha –value for each variable determines if the questions were measuring the same thing, therefore the reliability of the survey.

Reliability is seen to be in sufficient level, when the alpha is over 0,7, but over 0,95 is considered to be too high. This value is still questionable and the number of measured items affects the alpha. In this survey were three items and Cronbach's alpha of 0,80 the average interitem correlation is 0,57. With 10 items with the same alpha, interitem correlation would be 0,28. Cronbach's alpha is useful for item-specific variance when unidimensional values are used. This implies that there is little item-specific variance. (Cortina, 1993.)

The following Table 3 is calculated using SPSS and the amount of valid measurement units are displayed after the alpha value. The analysis tool excluded null values from the data, therefore excluding few occurrences. Using BIS –variable had 35 valid values, which is only two short from maximum, thus sufficient calculation. As Table 3 presents, every value is between requested 0,7-0,95 level, which implies the survey is reliable and sufficient for further investigation.

Table 3 - Cronbach's alpha

Variable	**Cronbach's alpha**
Usefulness	0,869, N = 37
Ease of use	0,889, N = 37
Accuracy	0,840, N = 37
Relevancy	0,873, N = 36
Vitality	0,905, N = 36
Insights	0,855, N = 36
Decision making	0,773, N = 36
Using BIS	0,793, N = 35

Cronbach's alpha for Ease of use –variable is especially interesting, because the variable had lowest average and the largest gap between minimum and maximum values. The alpha value of 0,889 indicates this is reliable variable and the variable had consistent answers for each participant.

4.1.2 Linear regression analysis

Regression analysis is a statistical analysis method for modelling and investigating relationship between variables. In linear regression model, there is independent variable and dependent variable, also known as predictor and response variable (Montgomery, Peck & Vining, 2012). R^2 value is calculated in SPSS –software and it is used to evaluate the predictive value between predictors and response. For 1,0, the predictor is completely similar to the response variable and vice versa 0 has absolutely no predictive value. R^2 can be seen as percentage, for example value 0,777 is 77,7%.

Figure 7 presents the outcomes of four regression analysis. The predictors are either Usefulness and Ease of use or Accuracy, Relevancy, Vitality and Insights. These predictors are calculated to respond to Decision making and Using BIS. Linear regression model can be used with multiple predictors and one response variable. As seen from the Figure 7, the R^2 values are from 0,631 to 0,777, with difference of 0,146 between the values. The both minimum and maximum values are between Usefulness and Ease of use to Decision making and Using BIS. This can be seen how users are more consistent how the predictor values affect response variables Decision making, versus Using BIS. One explanation why Using BIS has the lowest R^2 value is company environment, where employees do not have clear choice to use or not to use the system.

R^2 values between the second set of variables and Decision making and Using BIS are more consistent, with only 0,037 difference. These variables have moderately significant explanation level, but more interesting is to study the underlining reasons behind the minimum and maximum R^2 values.

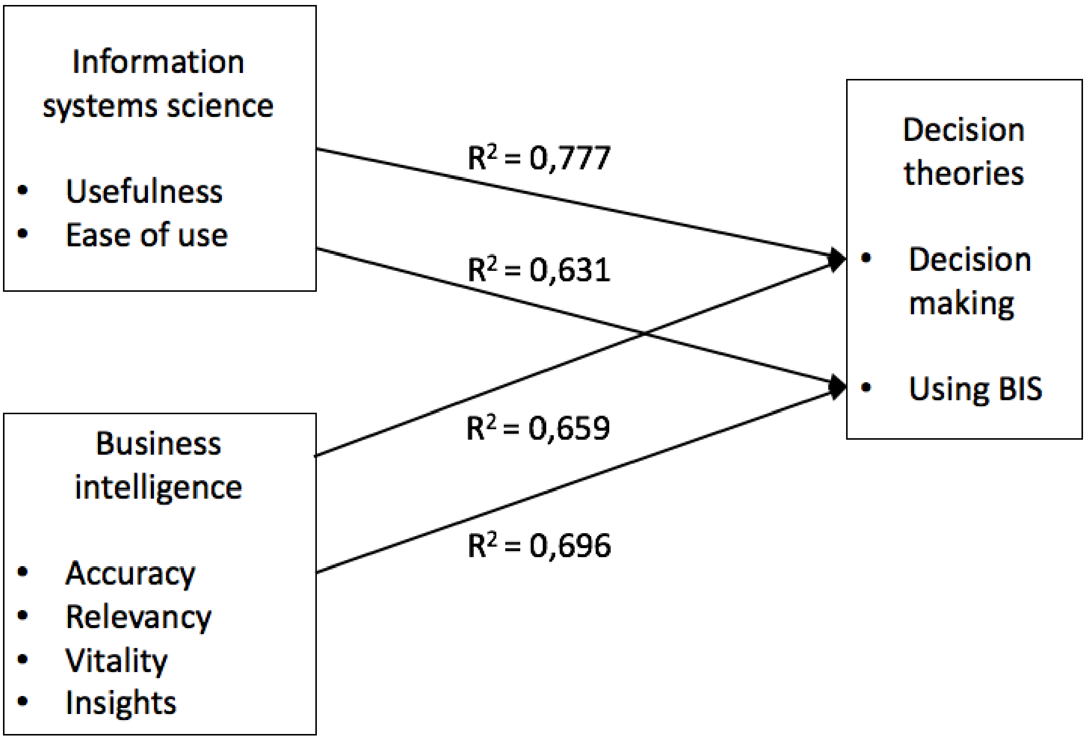

Figure 7 - Linear regression analysis

In Table 4 are presented regression analysis for four variables. Usefulness to Decision making has nearly douple the R^2 value compared to Ease of use to Using BIS. This supports the earlier explanation that users do not have an alternative to use, therefore lowering their Ease of use –variable, while supporting the usage. The amount of data is low for analyzing just one predictor and one response variable, lowering the significance of these. But when all of these are comparable with each other, the differences are the key in this table. The difference between the highest and lowest values is 51%, thus indicating how little Ease of use predicts Using BIS response compared to Usefulness and Decision making.

Table 4 - Regression analysis with single predictor values

Regression variables	**Value**
Usefulness to Decision making	0,666
Ease of use to Decision making	0,537
Usefulness to Using BIS	0,596
Ease of use to Using BIS	0,343

Figure 8 presents a scatter plot how the values are scattered, where Y axis is Ease of use. In X axis on the left is Using BIS variable and on the right Decision making variable. The plots are showing how much inconsistency there is among the values, which explains the lowest average for Ease of use and low R^2 value between Ease of use and Using BIS.

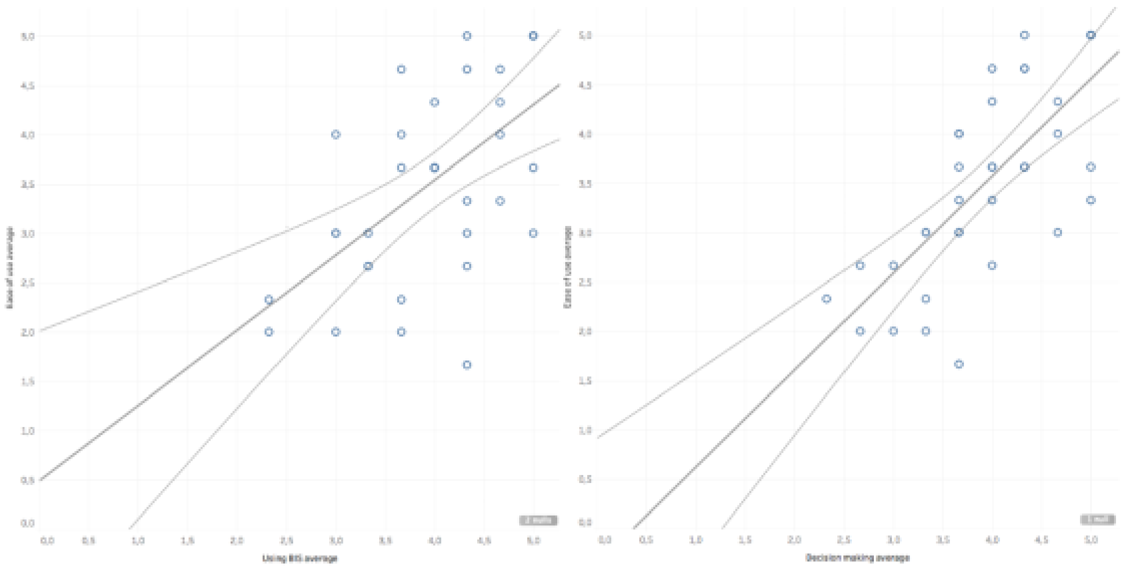

Figure 8 - Scatter plot with linear trend line. Ease of use with Decision making and Using BIS

Figure 9 has similar scatter plots, but the Y axis is Usefulness. Figure 9 shows much more consistent values and the trend lines have smaller width.

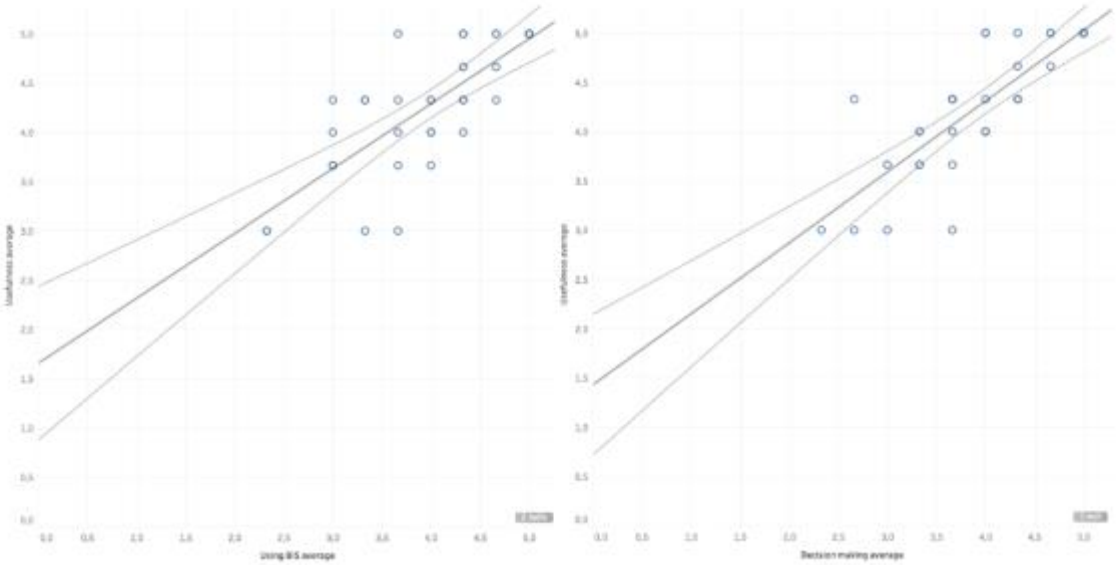

Figure 9 - Scatter plot with linear trend line. Usefulness with Decision making and Using BIS

Linear regression analysis provides a way to interpret how multiple value behave with each other. This analysis provided an insight how Ease of use and Using BIS have low R^2 value, indicating users' difficulties to use the system but the need to use it. Regression analysis provides a prediction, but in this case the predictive value is not relevant. For further studies the predictive pattern can be compared and evaluated.

4.1.3 Correlations

Correlation is a measurement unit used in statistics to determine the relationship between two or more variables. Correlation can be measured using Spearman's *rho* or Pearson's *r*, which in this case is Pearson's correlation model. Correlation can vary from -1 to +1 and values between 0,1-0,19 are nonexistent, 0,20 to 0,39 are weak, 0,40-0,59 are moderate, and above 0,60 are strong. It is vital to notice that correlation does not mean causality, but it indicates how the two variables are connected. After calculating the correlation, causal relationships can be investigated. (Faherty, 2008.).

The following three tables are calculated for investigation of how significant correlation there is in each group of interest. The groups are the same as in Figure 7: Information system science (Usefulness and Ease of use), Business intelligence (Accuracy, Relevancy, Vitality, Insights) and Decision theories (Decision making and Using BIS). Correlation seems similar to regression analysis, but correlation cannot produce predictions, thus focusing on the behavior between two variables along the data.

Table 5 presents a Pearson correlation between Ease of use and Usefulness from group Information system science. The r value is 0,611 with $p<0,000$ and N=37, thus strong. These two variables are the lowest and highest average, but Pearson's correlation does not reflect on that issue. When each participant answered in the six questions considering these two variables, the answers were correlating at 0,611 level. The underlying reason for this could be related how the users are seeing the usefulness, but not being able to meet the demands with the ease of use. These two variables are following each other among the participants and therefore difference in average does not restrict strong correlation.

Table 5 - Correlation between Ease of use and Usefulness

		EOUavg	UFNavg
EOUavg	Pearson Correlation	1	,611**
	Sig. (2-tailed)		,000
	N	37	37
UFNavg	Pearson Correlation	,611**	1
	Sig. (2-tailed)	,000	
	N	37	37

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6 is showing business intelligence group correlations and there are three relationships worth to investigate: Accuracy/Relevancy, Insights/Vitality and Insights/Relevancy. Correlation between Accuracy and Relevancy is strong: r=0,620, p<0,000 and N=36. Relevant data needs to be accurate, but accurate data is not necessarily relevant, which implies how the users are seeing that relevant data is always accurate. It is also questionable if users have encountered inaccurate data and how it has affected their work. Irrelevant data is easier to acknowledge, but it is not very reasonable to assume the irrelevant data to be inaccurate. Conclusion of this is to notice the correlation and the way the relationship most likely works: Relevancy before Accuracy.

Insights and Vitality have the weakest correlation: r=0,372, p<0,028 and N=35. Obtaining new insights from the data is according to this correlation statistic not a vital for the organization. Insights are seen relatively important (average ~3,8), but apparently the weak correlation indicates how the insights do not make the system more vital. There can be many reasons for this behaviour, but mostly it can be assumed to be the difficulty to gain advantage from them. Vitality is hard variable to explicitly explain in organizational context and there can be dozen of underlying reasons. Insights on the other hand are new revolutions from the data, but if they are hard to turn into actions, they do not necessarily increase vitality.

Insights have the highest correlation with Relevancy: r=0,683, p<0,000 and N=35. Obtaining insights from data requires the data to be suitable for the situation. Correlation between these two variables is presumed to be high, which suggests users are able to query relevant data and increase the insights gathered.

Table 6 shows nicely how the business intelligence group variables are correlating with each other. There are few reasonable investigation points, as seen, but overall the table is not providing new angle of analysis.

Table 6 - Correlation between Accuracy, Relevancy, Vitality and Insights

		ACavg	REavg	VIavg	INavg
ACavg	Pearson Correlation	1	,620**	,430**	,450**
	Sig. (2-tailed)		,000	,009	,006
	N	37	36	36	36
REavg	Pearson Correlation	,620**	1	,624**	,683**
	Sig. (2-tailed)	,000		,000	,000
	N	36	36	35	35
VIavg	Pearson Correlation	,430**	,624**	1	,372*
	Sig. (2-tailed)	,009	,000		,028
	N	36	35	36	35
INavg	Pearson Correlation	,450**	,683**	,372*	1
	Sig. (2-tailed)	,006	,000	,028	
	N	36	35	35	36

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Table 7, the Decision theories group containing Using BIS and Decision making. The correlation between these two is strong: r=0,829, p<0,000 and N=35. This r value is the highest of them all by a large margin, which can be investigated to shed light how these two are connected. Using a system designed for supporting decision making and finding a significant correlation between these two variables is an expected result. It is justified to assume when a user is using a system, thus increasing the amount of decisions made from the systems provided information.

Table 7 - Correlation between Using BIS and Decision making

		UBavg	DMavg
UBavg	Pearson Correlation	1	,829**
	Sig. (2-tailed)		,000
	N	35	35
DMavg	Pearson Correlation	,829**	1
	Sig. (2-tailed)	,000	
	N	35	36

**. Correlation is significant at the 0.01 level (2-tailed).

Pearson's correlation is a way to interpret deeper to the relationships between the variables, but causal relationships are harder to justify. Some assumptions can be made, for example using a system increases the decisions driven from it. Tables 5 to 7 are presenting statistics of the variables, but investigating the deeper associations needs have proper arguments. All the statistical models, Cronbach's alpha, regression modelling and Pearson's correlation are useful tools but careful justification behind the assumptions makes the arguments valid.

4.2 Data visualizations

The survey included total of seven background questions added to the 24 claims. These seven questions will be displayed using various data visualization styles provided from Tableau data visualization software.

Visualizing data is a part of business intelligence systems, hence visualizing data from the survey was done using Tableau –software. This software is used in organizations and two respondents answered the tool in their use. Data visualization is important factor to be used in business intelligence and enhancing visualization software was categorized as future investment area of BI (Watson & Wixom, 2007). Gartner categorizes interactive visualization as one of core capabilities among with OLAP, predictive modelling and data mining (Chen & Storey, 2012). The following presentations are designed to display various possibilities, but they are not necessarily the only way to present the data. One aim for this chapter is to show how these graphs work and justify why certain data types work with certain graphs better than others.

Figure 10 presents bar chart with added dots. Bar charts are very common way to visualize data, mainly because they are suitable for numeric values and the viewer can see the relationships between the values easily. Figure 10 is presenting overall average of the claims grouped by the role of the participants. Dots are added to each column to show the count of each role.

Average values do not have significant changes, but the count of analytics expert, consultant and secretary are two or less, which need to be excluded from the comparison. From business professional to executive roles the average values are from 3,6039 to 3,8363, mere 6% difference. Only statement from this chart is a slight increase of average for executives and management positions from business and IT professionals. 36 participants declared their role and secretary was the only non-predetermined role.

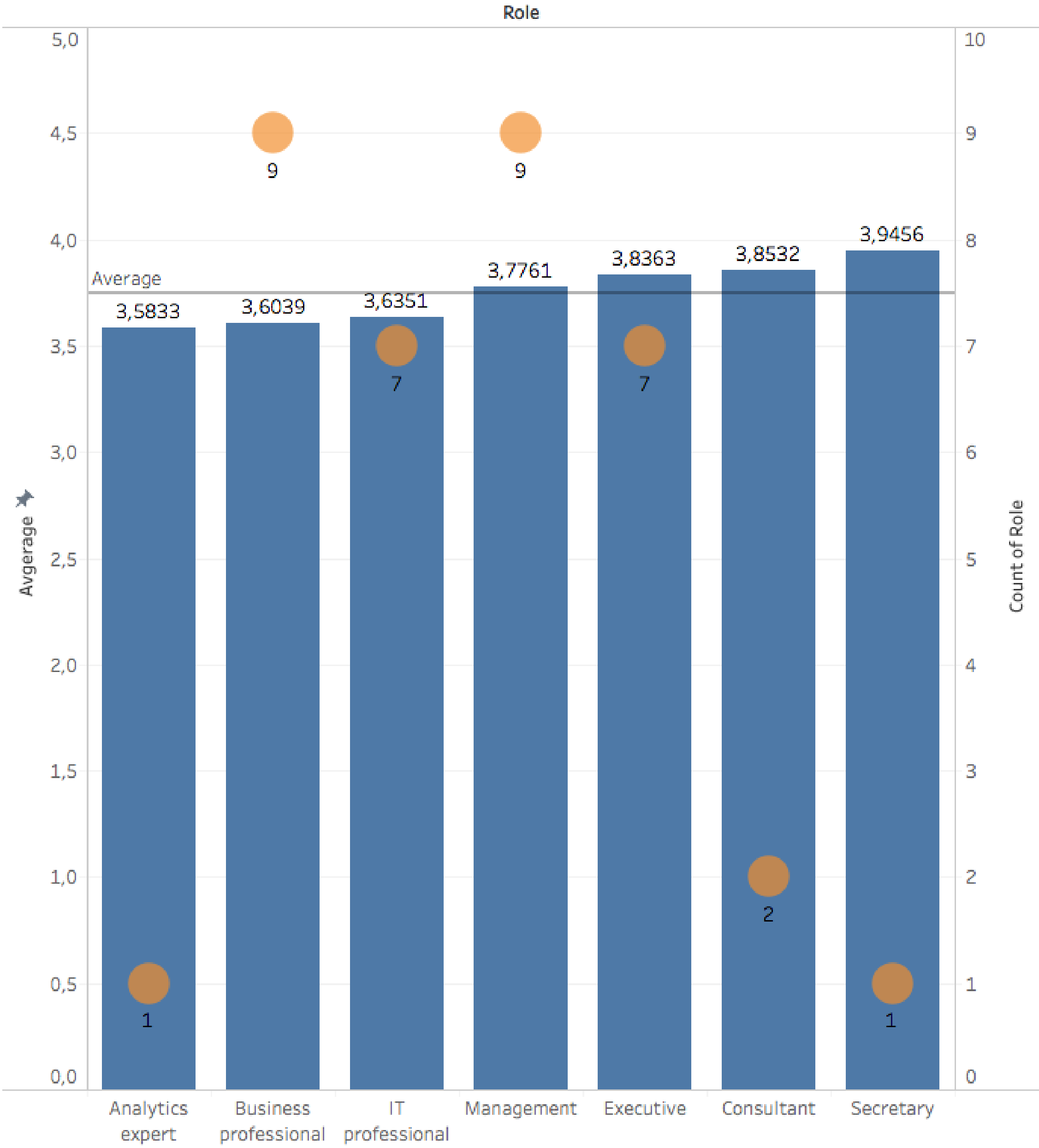

Figure 10 - Overall average by role with count of role

Figure 11 is a treemap of the systems the participants reported to use. This type of chart displays every value as area of total count. I.e. QlikView has 18 users and the percentage of total (46) is approximately 40%, therefore the area of QlikView tile is 40%. Colours are used to enhance the perceived relationship in the chart, as light cyan indicates value 1 and dark blue the maximum value.

This chart has exactly half of the values from a company Qlik (QlikView and QlikSense), which is caused by the cooperation with the consultant company providing their systems. Other providers are significant providers of organizational information systems (SAP, Microsoft, Oracle, Salesforce, IBM), smaller providers (Tableau, SAS) and others. Interestingly participants reported their systems vendor as programming languages R and Python, company named Savcor, which is providing corrosion protection enterprise resource planning software (Savcor, 2017). Company Workday is providing software for financial planning and human resources (Workday, 2017). Solita is Finnish IT company providing business intelligence solutions (Solita, 2017). Pentaho makes business analytics software (Pentaho, 2017).

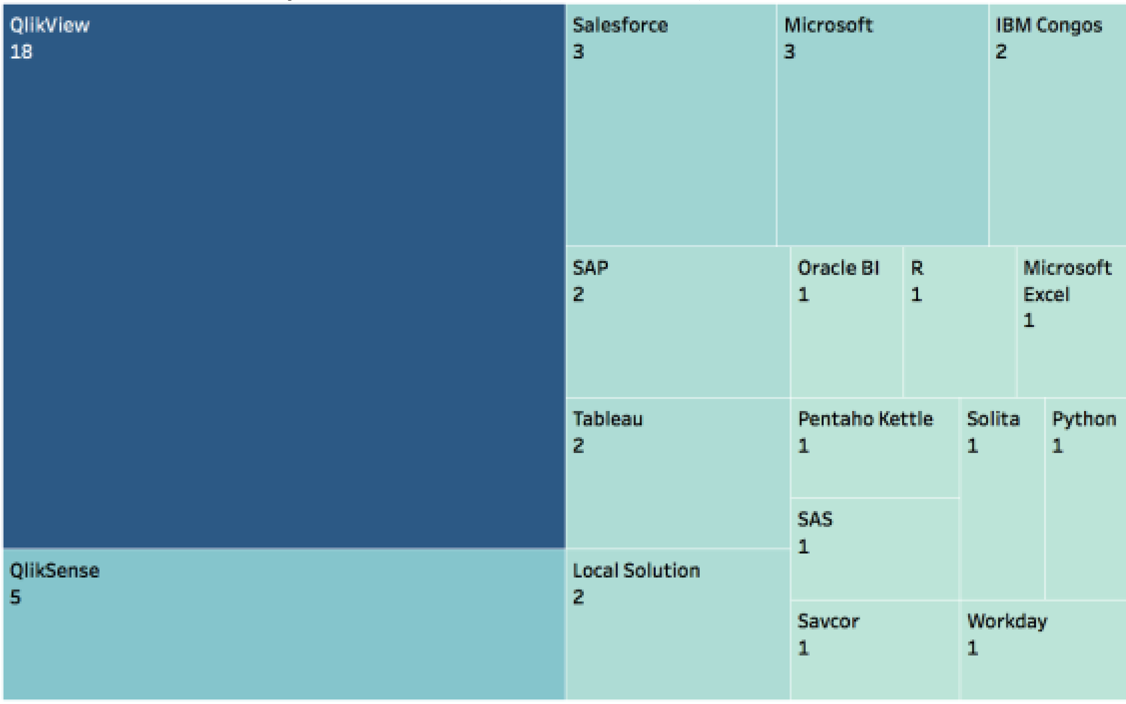

Figure 11 - Treemap of the systems in use with the total count

Figure 12 presents how many years the respondents have used any business intelligence system, in current or previous organization with the corresponding average of Ease of use for each duration. Less than 2 years is the most common answer and time used is rapidly decreasing after 5 years, which is not surprising result. Most of the companies are small to medium sized and business intelligence system has not been critical system for their organization. Experience of the system can be seen to affect the perceived ease of use, when the users have not been given a proper training. Perceived usefulness on the other hand is high, which can be a result of the effective marketing the vendors are practising or the systems have proven themselves in the short period of time, regardless that they are seemingly hard to use. Time is critical element when considering successful IT projects and this study could be made again few years from now to confirm if experience has positive correlation to Ease of use.

The figure 12 is displaying two variables and they can be compared easily. Usefulness –variable is not in the graph, because the averages were more consistent (0,56 to be difference) and therefore less explaining factor. Ease of use –variable is more interesting to analyse, but there is no clear increase of Ease of use when the user has been using the system for many years. The biggest gap is between the two longest used groups, resulting in 1,39 difference. The lack of respondents is affecting this result and therefore further studies are needed to confirm this issue.

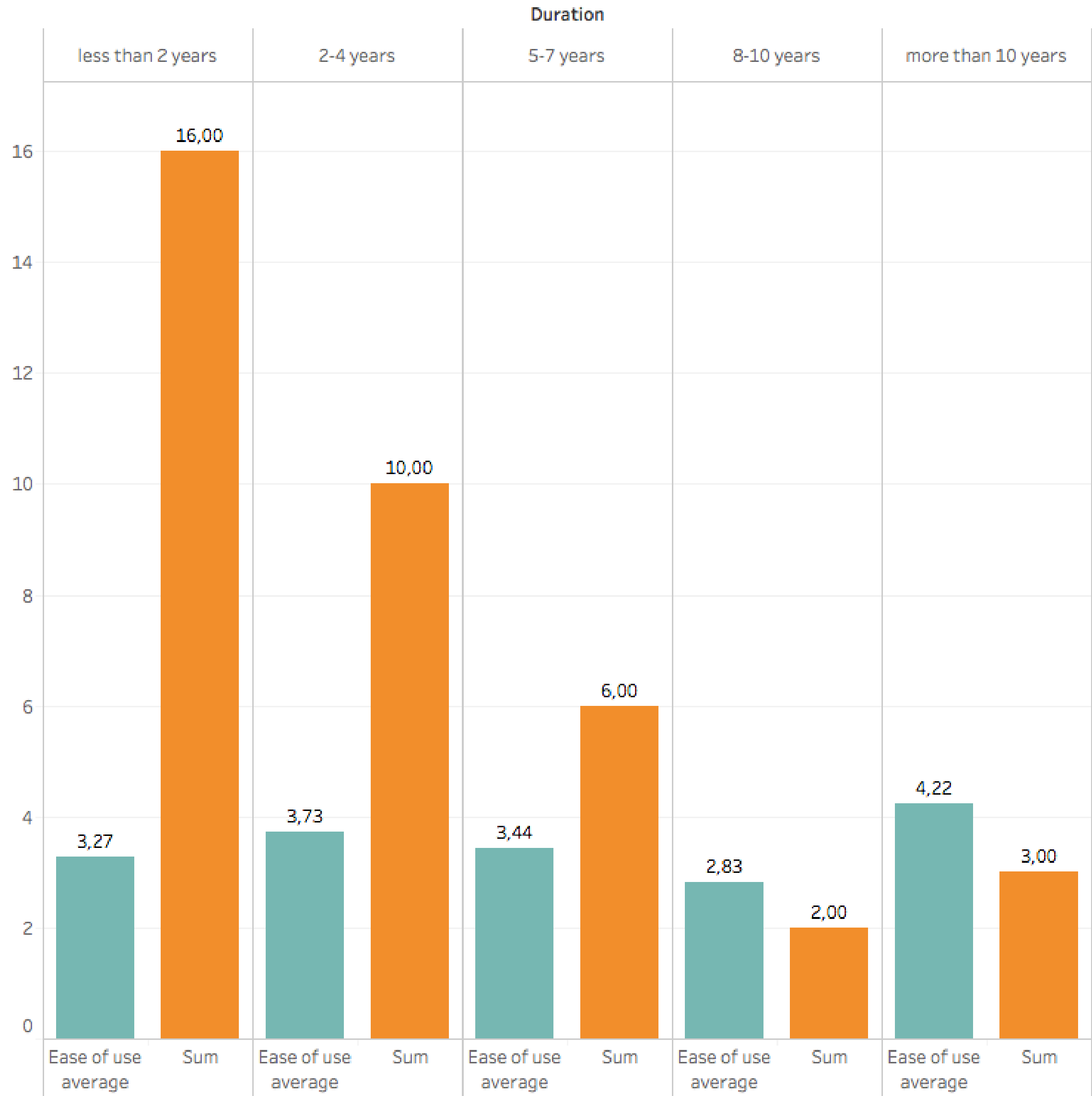

Figure 12 – Double bar chart with the count of duration and the average Ease of use

Figure 13 is more common pie chart, which is commonly used for presenting few values in a circle, where each section presents each value. The propositional dimensions are easily understood and in Figure 13 the most common answer, every day, has more than half of the area. This is encouraging result and it implicates the importance of the systems. Every day usage implicates the systems are part of daily decision making and monitoring of operations, which means the information gathered is valuable and actions are taken based on data. A few times a week is the second answer, with 11 answers. This amount of usage suits well for reporting and analysing past processes, which could lead to more refined changes in operations. A few times a month is clearly for reporting and bigger strategic decision making purposes. Monthly financial reports and decisions regarding the whole organization, which needs approval from the board of directors are most likely the use cases for users in this category. Option "A few time a year" did not get any answers.

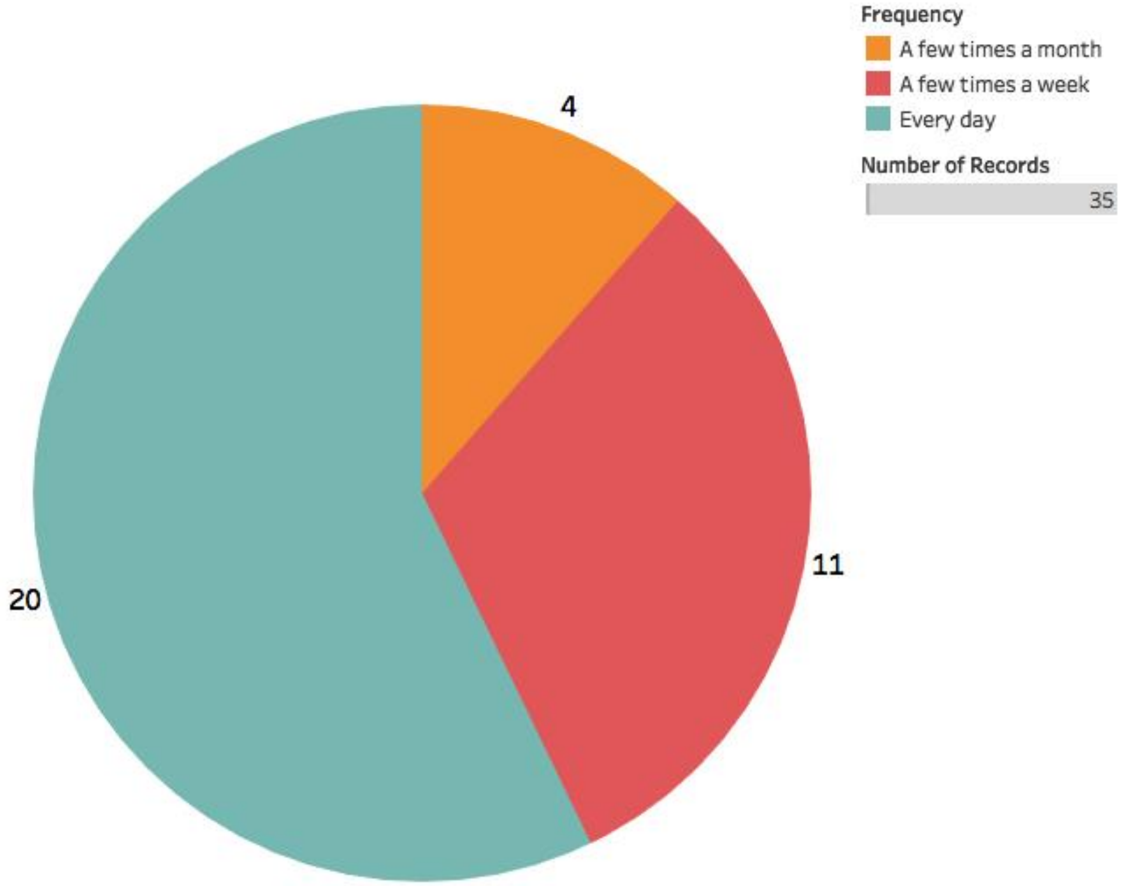

Figure 13 - Pie chart of the frequency of the systems usage

Table 8 is showing for what purposes the business intelligence system is meant to serve in organizations. The survey had seven choices to choose from and an empty space for own answer. Purposes with more than one answer was the predetermined and the rest were respondents own additions.

Improving operational efficiency and making better decisions were the most common answers, with 86% and 83% of total, respectively. These two factors are considered to be the main purposes according to the literature and apparently, the users have implemented these factors efficiently. The next most common answers, sales tool and identifying weak points, have 57% support and these factors are present in the literature, but they are not seen as significant. The field of the company determines slightly how well it can utilize the factors in their own organization, so this 57% support is well aligned with the proposed situation from the literature. The rest predetermined factors are present, but they are not meaningful for most the respondents.

The answers to the open answers are interesting, for example law is not present in the literature review and analytics is hugely present but most of the choices can be categorized to be part of business analytics –term. "To follow organizational KPI's" is present in the literature and is seen part of the real-time analytics. This issue could have been in the predetermined factors and might have resulted more answers. Reporting is present in the literature and business intelligence systems are well capable of reporting, however the systems have not focused on that issue due the advantages of ad hoc queries and prediction modelling. Overall the purpose of the system is well aligned with the proposed purposes gathered from the literature. Some unexpected results would need more elaboration, i.e. law, but with survey study it is not possible.

Table 8 - Purpose of the system and sum of the responses

Purpose of the system	**Sum**
Improving operational efficiency	32
Making better decisions	31
Sales tool	21
Identifying weak points	21
Identifying business trends	17
Revenue growth	13
Enhance market intelligence	8
Law	1
Business analytics	1
What If - modelling	1
Reporting	1
Analyze data in different views and aspects	1
To follow organizational KPI's	1
Customer base value	1

Figure 14 is another box-and-whiskers graph, which is based on Likert –scale for Content quality and Access quality. Respondents were asked to determine which one is more important and the answers were cancelling each other out. Likert –scale had options between 1 to 5 and the average is 2,243, which is 0,757 away from the middle. One noticeable fact is that none of the respondents answered the value 5. It is possible that the users were not fully aware what this question means in their case. This particular question was driven from literature, where systems direct of detail can be focused on each side. The result indicates users appreciate content quality more, but on contrary are not satisfied in ease of use. This leads to a situation where users are willing to make an effort to get the information, which they appreciate to be useful.

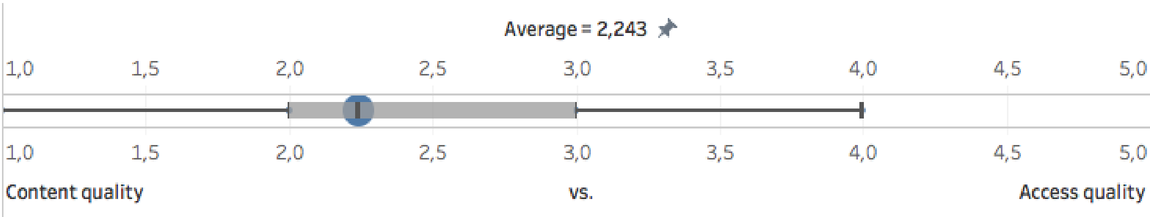

Figure 14 - Box-and-whiskers graph of comparison between content quality and access quality

Table 9 is the last question of the survey, an open question with aim to determine most important types of decisions. The most common answer was sales, which is present in the Table 8 on the third position. Some types are collected from the answers, for example optimization was answered for flights and tasks, thus grouped into one type. The table shows how diverse the decisions can be: from low level human resources to higher strategic decisions all the way to forecasting sales or trends.

Table 9 - The most important decisions made from BIS

Decision type	Sum
Sales	10
Financial (Balance sheet, profit & loss statement)	6
Manufacturing (warehouse, development)	6
Forecasting (Sales, trends)	4
Optimization (flights, tasks)	2
Operational	2
Strategy	2
Human resources	1

Data visualization is part of effective use of business intelligence systems and before graphs can be drawn the data have to be gathered, modified and cleaned. Some estimations say data visualization is 80% of the time working with the data and 20% of visualization. This happened to be close in this case, where cleaning the data and rearranging it was a major task. Sophisticated data warehouses can decrease the time for transforming data, when pre-calculations and grouping occurs automatically.

5 DISCUSSION

The literature review has introduced the field of study, the survey executed has been presented and analyzed extensively. Data has been visualized and assumptions have been made. This chapter will include discussion of the results and answering the research questions presented in the first chapter.

The main idea of this thesis is to research how businesses use their business intelligence systems. The survey study provided variety of answers, and Table 8 summarized the purposes the users identified. Literature review presented and survey data confirmed the main purposes: Improving operational efficiency, making better decisions, sales tool, identifying weak points and identifying business trends. These purposes are the most common and purposes expand to further areas as well: Human resources, organizational KPI's, customer base value and even law. Diversity of the purposes suggest business intelligence systems are useful for vast variety of companies.

Usefulness of any information system is essential, which was measured in the survey. Business intelligence was seen useful among the participants, with average of usefulness being ~4,2 when total average being ~3,9 on scale 1 to 5. Usefulness measured the highest average, which suggests users are seeing the benefits business intelligence systems are able to provide. Since the participants are mostly business-/IT professionals or management/executives, their opinions are not challengeable on contrary to vendor providers. As it turns out, ease of use was the least scoring variable with an average of ~3,5, which leads to an assumption if ease of use increases, usefulness increases as well. Pearson's correlation being strong supports this claim, but this issue needs further investigation.

Business intelligence systems are originating from decision support systems and they are still seen as such. Decision making measured 83% of the participants stating this as purpose, making it the second highest. The claims average for decision making is ~3,9, which is close to the overall average. The claims are ranging from 1 to 5, where 3,9 is a good result. Business intelligence systems are clearly a way to enhance decision making, but they are not restricted to this purpose. From company to company, the systems are modified for their needs and some companies may not be aiming to increase decision making.

The most used business area of business intelligence systems is sales. This decision category had 27% support among the respondents. Sales was seen as third common purpose with 57% of respondents claiming to use business intelligence system as a sales tool. Sales are important part of any company and apparently, decisions considering sales are the most used business area.

Users reported to focus more on content quality and result was ~2,2, where 3 would be middle point on scale 1 to 5. The users value the information the system offers and are willing to work for it. Organizational information systems are not usually seen as user-friendly, which might be taken for granted. Modern information systems are designed to be suitable for digital natives and are intuitive to use, without losing their core element: providing useful information. For business intelligence systems, it is essential to notice how the users are seeing the usefulness and are willing to make an effort to utilize it in their daily basis. Ease of use and access quality are issues worth fixing, but system providers have first made the systems essential. Future systems are seeing uses in mobile devices, where user interface is more important than in personal computer due the user input and size of the screen.

The main research questions are answered and the results overall were encouraging. The literature review offered many benefits and the systems in use in organizations reflect well with the promises. Some problems have risen, i.e. the survey could have included company KPI's as one predetermined purpose and the number of respondents should have been more than one hundred. Especially increasing the number of respondents would have gained more rich data, more convincing conclusions and increased the variety of companies. This survey can be determined as successful and with minor modifications reused with a different distribution channels to gain more responses.

Business intelligence factors are less present in the survey, because they might be harder for users to understand and analyze. Usefulness and ease of use are easier to determine good or bad, therefore they are more present in the graphs. Majority of users have been using business intelligence systems less than 2 years and they review them similar to enterprise resource planning (ERP) systems. These two systems are not significantly different, but where ERP is designed to provide facts from ongoing processes, BIS is designed to generate new information from those facts. Company integrating new BIS into their daily operations does not see the benefits the next day, therefore the survey should have reached more users with longer experience. Business intelligence is growing type of system and it is integrating technologies and ideas from all around the information systems field. It is a combination of data, humans and decisions. All of these aspects are interesting to study individually as well as together. This research has provided new information to the field, but more studies are needed to keep up with the technological development. The amount of data is not going to shrink.

6 CONCLUSION

Scientific research is often providing new insights and justified opinions. This thesis has not surprised what it comes to the results, but new questions have raised. The survey worked well with this research, although one limitation came from the lack of participants. This affected the justificatory issue with small amount of answers and the statistics are not as rich as they could be. This is considered as a limitation, not as a barrier to end the research as inadequate.

Academic field of business intelligence is vast and industry has influenced the academic work. In the process of writing the literature review, I came to a conclusion that the field of decision support systems is lacking well justified scientific theories, which would make more stable ground for this field. Companies such as IBM, Microsoft or SAP are producing their own products for companies but academic world is lagging to explain these complex system as they should be: clear theories and well justified models. Literature offered variety of advantages for companies and the survey confirmed the transition from academic work to system providers to end users.

The survey study is adequate for this kind of field and the variety of users provided interesting set of answers. The survey provided usable data and it was analysed with modern statistical models and visualized with modern tools to display some of the benefits proper visualization offers.

Research questions were answered with confidence the data provided and although the results were not surprising, they were yet convincing. Business intelligence systems benefit variety of business area i.e. operational efficiency and sales, they are useful and provide support to decision making. Sales are seen as the most used area of decisions driven from business intelligence systems and the second highest purpose of the system. Users report to appreciate more content quality over access quality, which gains support from usefulness to be more important factor than ease of use.

This thesis is providing a snapshot from the current state of perceived usefulness of business intelligence system in decision making process. Yet more research is needed for this expanding field: the relationship between usefulness and ease of use, effects of longer use of business intelligence systems, and case studies of usage behaviour in various fields.

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APPENDIX 1

PYYDÄ MUOKKAUSOIKEUTTA

Business intelligence survey

Welcome to participate to a survey about business intelligence usage. Please provide your answers with the best judgement for the best scienti<c validity. This survey is a part of Master's thesis in University of Jyväskylä.

This survey is designed for business intelligence system users from all around the organization. Consultants can answer, but if you don't have <rst hand knowledge, try to focus on the customers´ side.

Answering takes around 3-5 minutes.

This survey has three parts;

1. A few background questions.
2. A series of claims to assess how important business intelligence system is.
3. Couple of specifying questions.

Which of the following best describes your role in the organization?

Executive

Management

Business professional

IT professional

Consultant

Muu:

The main business intelligence system in your use (vendor or product name)

Oma vastauksesi

How many years you have used it? (in current and previous organizations)

less than 2 years

2-4 years

5-7 years

8-10 years

more than 10 years

How often you use the system?

Every day

A few times a week

A few times a month

Less than once a month

Once or twice a year.

Purpose of the BI system in your organization (can choose many)

Improving operational ef<ciency

Making better decisions

Revenue growth

Identifying weak points

Sales tool

Identifying business trends

Enhance market intelligence

Muu:

The next section includes a series of claims

1 means completely disagree
3 means neutral
5 means completely agree

If you don't have any opinion, you can skip the claim.

I think that the business intelligence system I use is useful.

	1	2	3	4	5	
Completely disagree						Completely agree

I consider that the business intelligence system I use helps my decision making.

	1	2	3	4	5	
Completely disagree						Completely agree

I believe that I get exact information from the system.

	1	2	3	4	5	
Completely disagree						Completely agree

I get the information I need easily from our system.

	1	2	3	4	5	
Completely disagree						Completely agree

Business intelligence system is vital for my organization.

	1	2	3	4	5	
Completely disagree						Completely agree

Business intelligence system has brought new information, which I haven’t been looking for previously.

	1	2	3	4	5	
Completely disagree						Completely agree

I believe I get relevant information from the system.

	1	2	3	4	5	
Completely disagree						Completely agree

I use frequently business intelligence system when deciding actions.

	1	2	3	4	5	
Completely disagree						Completely agree

Our performance would hurt without business intelligence system.

	1	2	3	4	5	
Completely disagree						Completely agree

I am sure that the business intelligence system I use gives me valuable information.

	1	2	3	4	5	
Completely disagree						Completely agree

Information I get is highly related what I was looking for.

	1	2	3	4	5	
Completely disagree						Completely agree

Decisions I make are more con<dent because of business intelligence system.

	1	2	3	4	5	
Completely disagree						Completely agree

Information I am looking for can be found easily.

	1	2	3	4	5	
Completely disagree						Completely agree

I trust that business intelligence system gives me accurate information.

	1	2	3	4	5	
Completely disagree						Completely agree

I have found new insights by using business intelligence system.

	1	2	3	4	5	
Completely disagree						Completely agree

Business intelligence system allows me to do better decisions.

	1	2	3	4	5	
Completely disagree						Completely agree

I understand deeper associations after using business intelligence system.

	1	2	3	4	5	
Completely disagree						Completely agree

Decision I have made with the help of business intelligence system has been better than without it.

	1	2	3	4	5	
Completely disagree						Completely agree

I have always found the information I have been looking for.

	1	2	3	4	5	
Completely disagree						Completely agree

Our business intelligence system gives me precise information.

	1	2	3	4	5	
Completely disagree						Completely agree

Choices I make are supported greatly by business intelligence system.

	1	2	3	4	5	
Completely disagree						Completely agree

I consider that the business intelligence system I use is bene<cial.

	1	2	3	4	5	
Completely disagree						Completely agree

Business intelligence system offers me pertinent information.

	1	2	3	4	5	
Completely disagree						Completely agree

Business intelligence system is essential for my organization.

	1	2	3	4	5	
Completely disagree						Completely agree

Which one of these is more important to you?

	1	2	3	4	5	
Content quality						Access quality

Please specify three most important types of decisions you make. (E.g. sales, manufacturing)

Oma vastauksesi

Add an email address to get summary of the results (estimated March, 2017). This email address will not be used anything else than this purpose.

Oma vastauksesi

LATAA

Älä koskaan lähetä salasanaa Google Formsin kautta.