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Predictive Analytics – Examining the Effects on Decision Making in Organizations

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Abstract:

Predictive analytics is a type of business analytics which enables predictions to be made, about occurrence of particular events in the future, based on data of the past. The predictive analytics is widely incorporated among the most successful organizations where it supports their decision-making process.
The aim of our study is to examine the effects on decision making in organizations caused by predictive analytics. We perform a qualitative study to investigate the effects by using Simon's model to break down the decision-making process and analyse how the predictive analytics affects each stage. Additionally we test the propositions from Huber's theory of the effects of advanced information technology on organizational design, intelligence and decision making, in the context of predictive analytics as an advanced information technology. Our contribution to IS knowledge is derived from our findings which show that the predictive analytics offers strong support in the intelligence and design phase of the decision-making process, while having no effect on the choice phase. Furthermore, through the prism of Huber's theory, we find that the predictive analytics generates effects on the organizational intelligence and decision making, while also having effects at subunit level, organizational level and the organizational memory.

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Fadi Makhoul

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1 Introduction

Information Systems research community argues that Business Intelligence (BI) today is omnipresent in organizations, a technology that successful organizations utilize. Even though the name Business Intelligence appears to be relatively new by various sources, the main idea behind it dates several decades back to decision support systems (Hosack et al, 2012; Negash, 2004; Watson, 2009). With regards to what Business Intelligence is, Negash (2004, p.178) gives the following definition:

“Business Intelligence 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 Analytics (BA) on the other hand, is considered to be the next evolutionary stage by information systems research community, a trend that will replace business intelligence while bringing the focus to big data and analytics (Hosack et al, 2012). Business analytics as an emerging field can ultimately lead to improved decision making, by providing a better understanding of business dynamics (Schläfke et al., 2012). Despite that, authors in literature use both terms business intelligence and business analytics for referring to the same ideas that the Negash’s (2004) definition explains. Yet, other authors in IS literature found a reasonable compromise using the term Business Intelligence and Analytics (BI&A) while still referring to the Negash’s (2004) definition with the focus on the analytics part.

As an answer to the question what BI&A actually does for organizations, Negash (2004) states that it assists them in strategic and operational decision making by converting data into information and ultimately into knowledge via analysis done by people. Modern organizations nowadays simply must be competing on analytics, especially in the areas of predictive analytics (Davenport, 2006). Some of the “sources of strength” for organizations competing on analytics, as Davenport (2006) states are the following: the right focus, the right culture, the right people and the right technology in terms of powerful business intelligence software and computing hardware. Organizations adopt analytical approaches as a way to cope with data, empowered by its constant growth and availability, resulting with development of advanced data analysis, scenario planning and predictive capabilities as means for fighting increasing complexity, uncertainty and volatility (Schläfke et al., 2012).

Predictive business analytics (or predictive analytics) is a special type of business analytics (Boyer et al., 2012) which is practiced by the most profitable organizations that are best players within an industry (Davenport, 2006; Siegel, 2013). What predictive analytics does is it “enables users to predict what will happen next in order to make better decisions for future outcomes” (Boyer et al., 2012, p. 147). In addition to that, predictive analytics is dependent on data from which hidden predictive information is extracted so that various relationships are better understood and knowledge is generated to support decision making in organizations (O'Flaherty and Heavin, 2014).

1.1 Problem area and research question

"Organizations are competing on analytics not just because they can - business today is awash in data and data crunchers - but also because they should" (Davenport, 2006, p.1).

Organizations exist in a world where big data is omnipresent and available for them, growing and developing more than ever (Chen et al., 2012; McAfee and Brynjolfsson, 2012).Organizations within an industry offer relatively similar products, using similar technologies and it is their business processes and knowledge they obtain from their data that will differentiate them from others and help them get the biggest share of the profit (Chen et al., 2012; Davenport, 2006; Wixom et al., 2011; Wixom et at., 2013).

Predictive modelling and analytics can be of crucial importance for organizations if correctly aligned with their business process and needs and can also lead to significant improvement of their performance and quality of the decisions they make, thus increasing their business value (widely known examples of organizations are retailers like Amazon and EBay and targeted online ads networks like Google and Facebook) (Davenport and Kim, 2013; Siegel, 2013). Every organization can statistically analyse their data and get to know their environment better to some extent (their current clients, profit movements, track of supplies and so on), but the biggest potential for profit lies among those who are able to perform predictive modelling thus identifying the most profitable courses of action and make decisions based on them (Davenport, 2006; O'Flaherty and Heavin, 2014).

Despite the success stories of incorporated predictive analytics by practitioners (Rjeily and Reilly, 2012; CGI Group, 2013; SAP, 2013) and big tangible and measureable benefits to organizations (Siegel, 2013), information systems researchers as well include the meaning and importance of predictive analytics when discussing the future trends and evolution of decision support systems (Davenport, 2006; Hosack et al., 2012).

While the area of making predictive analysis is a very hot topic for researchers in the fields of computer science, mathematics and statistics, that is not the case for the Information Systems research community. Information systems literature review about the existence of predictive analytics shows that only 52 articles were identified as relevant between the years of 1990 and 2006 (Shmueli and Koppius, 2010).

Since predictive analytics plays a big role in the most profitable organizations and also represents a trend which organizations follow, it is to be considered an important segment in the support of decision making. In addition to that, IS research already done in areas associated with predictive analytics is very limited, thus it is indeed the case that new opportunities are open for further research to be conducted.

Therefore, the research question that we propose is:

- *What are the perceived effects of the use of predictive analytics on decision making in organizations?*

1.2 Purpose

Data and business analytics tools are particularly useful for organizations because of the support they offer for decision making, considering the fact that decisions based on data and made with the use of analytical tools are normally better than those made without (Klatt et al., 2011; Schläfke et al., 2012). That signifies the big importance and potential that business analytics has for organizations as a whole. The use of business analytics most evidently adds value to the organization at certain level. Organizations that are characterized with superior performance typically adopt and use business analytics in an intensive way (Klatt et al., 2011) when compared to others, while the best performers incorporate predictive analytics (Davenport, 2006; Siegel, 2013).

The reason why we propose this study is because predictive analytics, as an area under the umbrella of business analytics, is still an under-researched area within the IS community and we would like to examine its potential and influence within the context of decision making in organizations. The problem area is within the domain of IS because it explores the effects from an IT artefact in relation with organizational and business processes as is the decision making.

The purpose of our research is to study the perceived effects of the use of predictive analytics on decision making in organizations and thus generate knowledge to the research community. The research will be done on organizations that rely on predictive analytics for decision making. The results are expected to show what effects of the use of predictive analytics are perceived to be present in the decision-making processes, in what form and in what aspect of the decision making.

1.3 Delimitation

Business intelligence and analytics are broad areas and in our study we will only focus on predictive analytics, as a particular type of business analytics. Our study will not analyze the technical details that exist in terms of characteristics, implementation of various tools and algorithms that are being used in order to enable predictive power.

Decisions are categorized in multiple groups by different dimensions in literature. In our study we will not focus on particular type of decision that is made on a certain level within the organizations. Instead, we are interested in the decision making as a process, regardless the type of decisions.

2 Literature Review

Having introduced our problem area, research question and purpose of our study, in this chapter we dig deeper in the theoretical background of our study. We extend the context of our research which we introduced in the previous chapter by referring to relevant existent IS discussions. First we are going to elaborate what predictive analytics represents and where it originates from. Second, we discuss what decision making is in the context of organizations, to provide a foundation of the theoretical frameworks that we next discuss. Finally, we present and motivate our choice of frameworks we focus on, which are Simon's model of the decision-making process and Huber's theory of the effects of advanced information technologies on organizational design, intelligence and decision making. We conclude this chapter by presenting our theoretical framework which we are going to use in order to answer our research question.

2.1 From BI to BA to Predictive Analytics

Business intelligence (BI) is defined in various ways in information systems literature. Some authors see it as a process or a sequence of processes (Golfarelli et al, 2004) where data is analysed, relationships are discovered and knowledge is generated to facilitate decision making in organizations. Other authors see business intelligence as both a process and a product, where the product is information or knowledge for decision making (Martinsons, 1994). Furthermore, there are authors who see business intelligence as a process, product and technologies, where definitions include working with data using analytical tools as one of the key components to generate information for decision makers (Clark et al., 2007). All in all, the purpose of BI is to provide the right information, in the right format and in the right time to the right users so that the performance of the company is improved in terms of decision making (Negash, 2004).

Historically speaking, business intelligence evolved from decision support systems (DSS) in the late 1980s and early 1990s (Power, 2007). However, the history of decision support systems dates back to 1960s and their historical evolution has been analysed by Arnott and Pervan (2005) who built a timeline, which is later to be updated by Hosack et al. (2012), as displayed in Figure 2.1 .

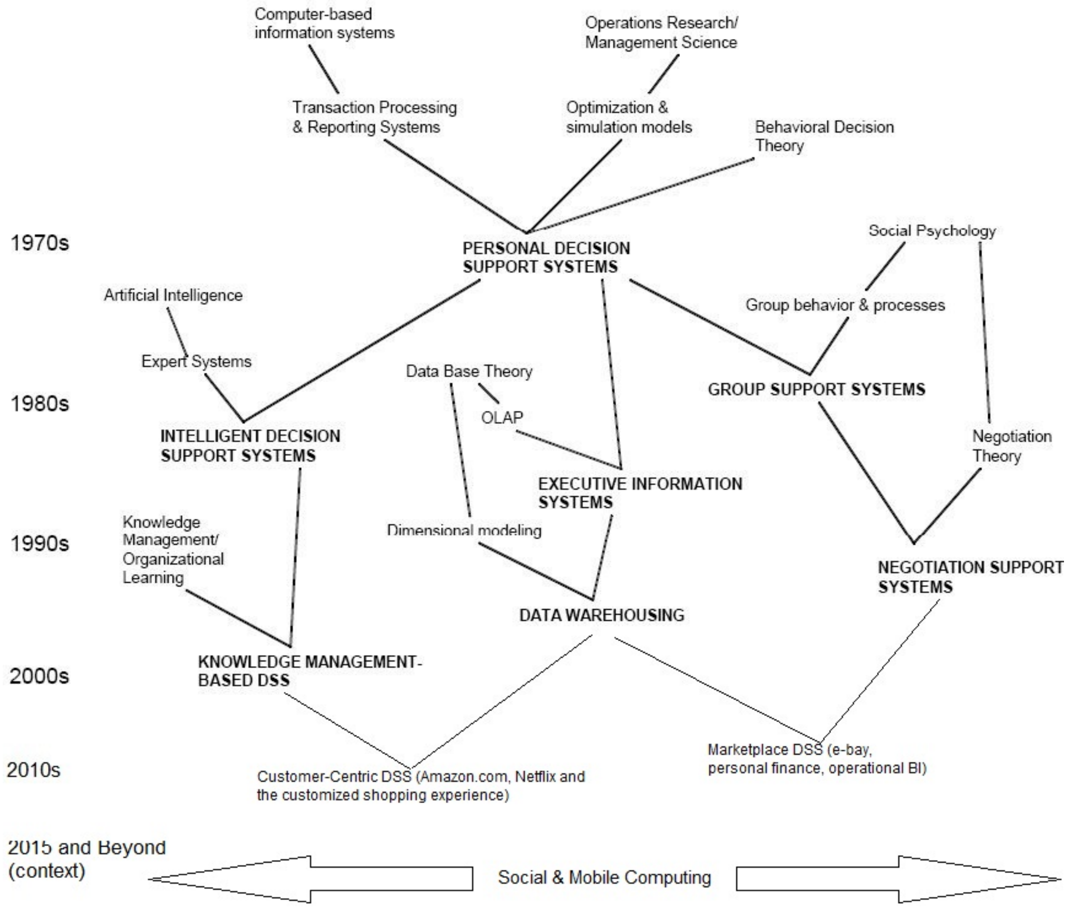

Figure 2.1 History of DSS according to Hosack et al. (2012)

We already went through the various definitions concerning BI in IS literature and made a trip through DSS evolution history, to familiarize with the context of business intelligence. In addition to that, in order to extend the context of BI we present a generic BI environment (Figure 2.2) as developed from literature review by Watson (2009). The generic BI environment is applicable enterprise-wide and provides a picture of the all the processes, connecting data integration and access technologies and processes, together with governance and data quality processes to be able to support decision-makers when using BI technologies and applications.

Business analytics (BA) on the other hand, is seen as a next evolutionary stage, a more advanced discipline, a term that is going to push aside and replace business intelligence (Laursen and Thorlund, 2010). Additionally, BA is well associated with big data and advanced analytics (Hosack et al, 2012). Furthermore, authors use the term Business Intelligence and Analytics (BI&A) to refer to a combination of the processes in the Negash's (2004) definition and advanced analytics (Chen et al., 2012).

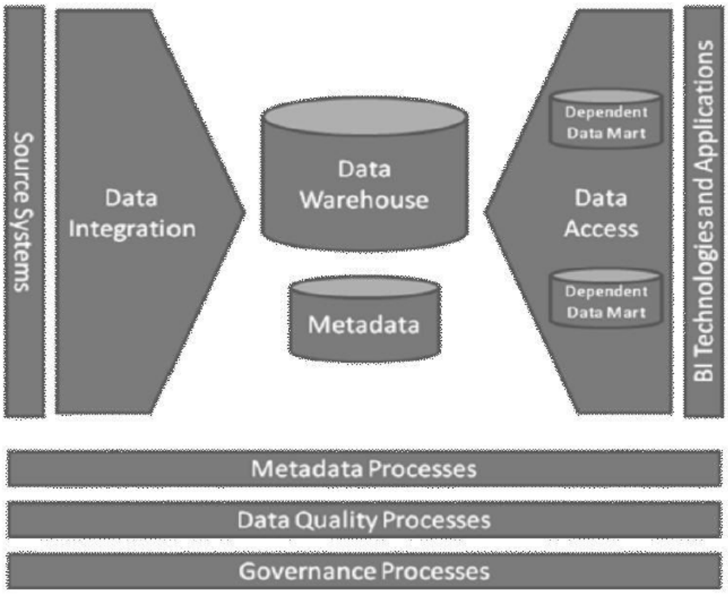

Figure 2.2 Generic BI environment (according to Watson, 2009)

Answering the question why business analytics is more and more embraced by organizations, Klatt et al. (2011) argue that three factors exist that are key promoters of business analytics:

- *data overload* - business analytics presents relevant and reliable information for decision makers out of the big pool of data
- *causal interdependencies* - business analytics identifies relationships between complex impact factors thus leading to improved decision making
- *holistic application* of business analytics - relates to the “managers’ awareness of critical interdependencies between inputs, processes, outputs and outcomes”.

Both Klatt et al. (2011) and Schläfke et al. (2012) suggest a multi-layer framework that explains integration of business analytics into performance management within the organizational context. The purpose of the framework is to provide guidance for managers when they need to decide what kind of analytics is most suitable for them to use by mapping the “causality-based couplings of context factors, inputs, processes, outputs and outcomes in order to highlight their value creation” (Schläfke et al., 2012, p.116).

The only way to get the most effective business analytics is to combine these areas of expertise within the organization:

- *IT*: data mining, natural language processing, classification, regression trees etc.
- *Strategic management accounting*: cost break down and driver analysis, process modeling, total cost of ownership, balanced scorecard, life cycle costing etc.
- *Analytical methods*: econometric, mathematical and statistical like regression analysis, structural equation modeling, vector autoregressive modeling and so on (Schläfke et al., 2012).

Some of the large numbers of potential BI&A users are: analysts, information workers, managers and executives, suppliers, customers and regulators, front line workers and IT developers (Watson, 2009). Negash (2004, p. 179) refers to a Gartner study that ranks the strategic use of business intelligence like:

- corporate performance management
- optimizing customer relations, monitoring business activity and traditional decision support
- packaged standalone BI applications for specific operations of strategies
- management reporting of business intelligence.

Additionally BI&A is used for creating forecasts and estimates based on data, creating and observing the outcomes from "what if" alternative scenarios, getting answers to ad-hoc non-routine questions and getting strategic insight (Negash, 2004). Despite the fact that many organizations practice analytics in one way or another to facilitate their business processes and especially the decision making, not many have achieved a level of proficiency (Davenport, 2006). Furthermore, some of the other types of information systems that BI&A is related to are: Online Analytical Processing (OLAP), data warehouse, visualization, Customer Relationship Management (CRM) marketing, Geographic Information Systems (GIS), knowledge management, DSS/ Executive Information Systems (EIS) and data mining (Negash, 2004).

2.1.1 Predictive analytics

Having discussed what business intelligence is, how it is related to business analytics and how important it is to organizations, we will narrow down our research problem area and focus on one particular segment of interest to our study - which is the predictive analytics.

Analytics is related to "the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and add value" (Davenport and Kim, 2013, p3). According to the differences in the analytical methods used as well as the purpose they are being used for, analytics can be divided into the following categories: descriptive, prescriptive and predictive. The *descriptive analytics* can be referred to as reporting and it describes a certain phenomenon of interest. It includes the actions of gathering, organizing, tabulating and depicting data, and even though it is useful for decision makers in the context of an organization, it does not provide details about why certain event occurred nor it is able to say what could happen in the future (Davenport and Kim, 2013; Delen and Demirkan, 2013; Song et al., 2013). The *prescriptive analytics* on the other hand, is related to making suggestion about a certain set of actions and includes methods of experimental design and optimization (Davenport and Kim, 2013; Sharda et al., 2013; Song et al., 2013). The experimental design explains the reasons why a phenomenon occurs by making experiments where independent variables are manipulated, extraneous variables are controlled and therefore conclusions are being made which result with actions that the decision maker should practice. Optimization as a technique suggests balancing the level of a certain variable related to other variables, thus identifying the ideal level of it – a recommendation for the decision maker (for example identifying the ideal price of a product to be sold, the ideal level of supplies to be kept in inventory or the right quantity of a particular order to be made) (Davenport and Kim, 2013).

Finally, *predictive analytics* is about determining the events which would happen in the future with a certain likelihood (Brydon and Gemino, 2008; Boyer et al., 2012; Davenport and Kim, 2013; Delen and Demirkan, 2013; Schmueli and Koppius, 2010; Sharda et al., 2013; Siegel, 2013). The predictive analytics "go beyond merely describing the characteristics of the data and the relationships among the variables (factors that can assume a range of different values); they use data from the past to predict the future" (Davenport and Kim, 2013, p. 3). In order to make it more clear for the reader to understand what predictive analytics refers to, what events are being predicted and what results are being achieved, in Table 2.1 we present a brief summary of examples introduced in Siegel's (2013) book.

Table 2.1 Examples of predictive analytics

What is predicted	Area	Who predicts?	Results
Location - where you will be	Family and Personal Life	Nokia	Location is predicted one day beforehand within 20 meters in average
Friendship	Family and Personal Life	Facebook LinkedIn	Precise suggestions to improve your connections with people.
Love	Family and Personal Life	Match.com OkCupid	Intelligent matching in online dating
Divorce	Family and Personal Life	Clinical researchers	Predict divorce with 90% accuracy
Purchases in ordered to target marketing	Marketing and advertising	Target	Increased revenue 15-30 % with predictive modelling
Cancelations in order to retain customers	Marketing and advertising	Telenor	Reduced cell phone subscriber turnover by 36%
Product choices for personalized recommendations	Marketing and advertising	Amazon	35% of sales come from product recommendations
Non-payment	Financial risk and insurance	DTE Energy	700% increase in net savings
Breast cancer	Healthcare	Stanford University	Build a predictive model that diagnoses breast cancer better than human doctors, considering number of facts
Job performance	Staff and employees – Human Resources	US Special Forces	Predict which candidates will be successful in the demanding job that are worth investing in years of training
Dropouts	Education	Netherlands' Eindhoven University	Predict which students are likely to drop out and assist them to prevent that

Davenport and Harris (2007) position the predictive modelling and analytics within the domain of BI&A based on the dimensions: degree of intelligence and the competitive advantage it gives to the organizations that are using it Figure 2.3.

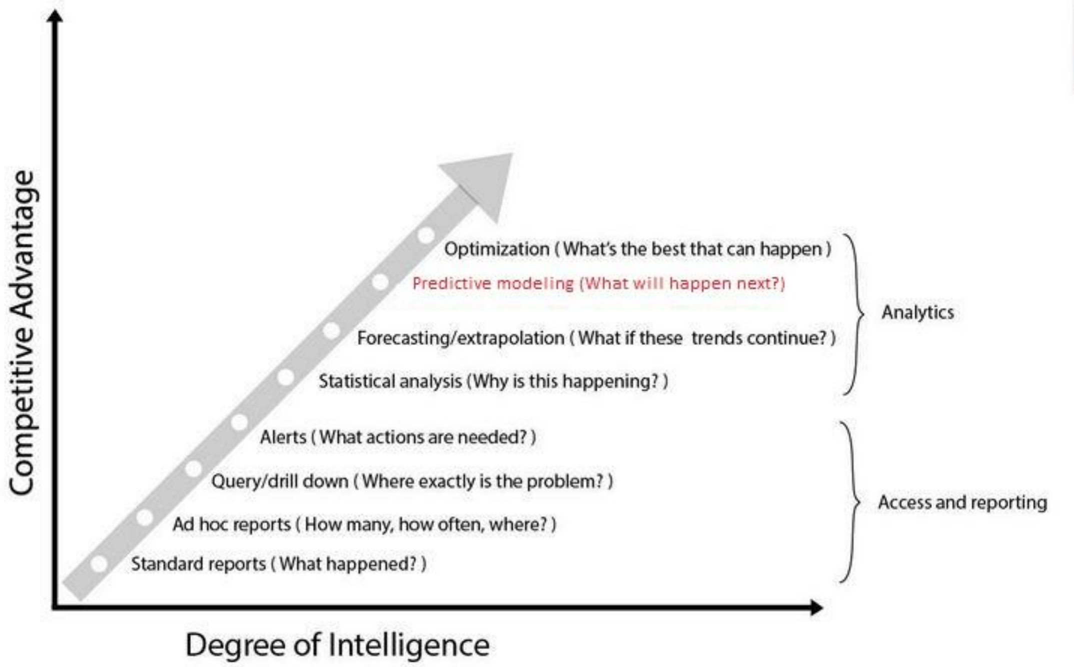

Figure 2.3 Predictive analytics and modelling positioned in BI&A context (Davenport and Harris, 2007)

Predictive analytics refers to "building and assessment of a model aimed at making empirical predictions" in the context of quantitative empirical modelling (Shmueli and Koppius, 2010, p. 555). That includes empirical predictive models (statistical models like data mining algorithms for instance) which predict future scenarios and evaluation methods assessing the predictive power of a model. What predictive analytics does is identify relationships between the variables and after that, based on those relationships it predicts the likelihood for a certain event to occur. Despite the predictive purpose the relationships between data are used for, explicit cause-effect relationships are not expected or assumed to be present in the data (Davenport and Kim, 2013).

Empirical modelling for explanation refers to statistical models that are used for "testing causal hypotheses that specify how and why certain phenomena occur" (Shmueli and Koppius, 2010, p. 554). That includes explanatory statistical models for testing hypotheses (like regression models, common in IS research and social sciences in general) and methods for evaluating the explanatory power of the model (various statistical test for strengths of relationships). Shmueli and Koppius (2010) point out to the existence of large debate about the difference between explaining and predicting and their research results with explaining the differences between these two terms in five different steps: analysis goal, variables of interest, model building optimized function, model building constraints and model evaluation in Table 2.2.

Table 2.2 Explanatory Statistical Modelling and Predictive Analytics according to Shmueli and Koppius (2010)

Step	Explanatory	Predictive
Analysis Goal	Explanatory statistical models are used for testing causal hypotheses.	Predictive models are used for predicting new observations and assessing predictability levels.
Variables of Interest	Operationalized variables are used only as instruments to study the underlying conceptual constructs and the relationships between them.	The observed, measurable variables are the focus.
Model Building Optimized Function	In explanatory modelling the focus is on minimizing model bias. Main risks are type I and II errors.	In predictive modelling the focus is on minimizing the combined bias and variance. The main risk is over-fitting.
Model Building Constraints	Empirical model must be interpretable, must support statistical testing of the hypotheses of interest, and must adhere to theoretical model (e.g., in terms of form, variables, specification).	Must use variables that are available at time of model deployment.
Model Evaluation	Explanatory power is measured by strength-of-fit measures and tests (e.g., R2 and statistical significance of coefficients).	Predictive power is measured by accuracy of out-of-sample predictions.

Predictive analytics in IS literature

Information systems literature review about the existence of predictive analytics in literature was conducted by Shmueli and Koppius (2010) by querying the terms predictive, predicting, forecasting, predict, prediction and predictor in MIS Quarterly and Information Systems Research (ISR) journals, between the years of 1990 and 2006. After manually filtering the initial 250 returned papers and eliminating the ones that use those keywords for no predictive goal or analysis, authors identified 52 relevant articles in literature which they classified in four categories by two dimensions: predictive goal – adequate, predictive goal – inadequate, predictive assessment –adequate and predictive assessment – inadequate. What they found based on the literature review is the following: “empirical predictive goals and claims are rare” and “predictive analytics are rare” because only 7 from the 52 articles incorporated predictive analytics while the other derived predictive power from explanatory power (Shmueli and Koppius, 2010, p. 560). Though the initial critic of those findings would be that authors only searched through two information systems journals while excluding other important journals, the presented numbers are rather sufficient to illustrate the limitation of IS literature when it comes down to researching areas related to predictive analytics within IS.

Analysing the value that predictive analytics delivers to information systems research, Shmueli and Koppius (2010) identify six roles that predictive analytics can have: generating new theory, developing measures, comparing competing theories, improving existing models, assessing relevance and assessing predictability. These roles can serve as means to help practitioners and researchers when working with predictive analytics.

2.2 Decision making

In the previous section we went through what business intelligence and business analytics are, stating that the focus of our study will be on predictive analytics as a special type of business analytics. One of the points that we wanted to make is that business intelligence, business analytics and predictive analytics as well, serve the purpose of facilitating the decision making in organizations. In this section we will be more specific about what decisions and decision making are, to be able to get a clearer picture of the connection with predictive analytics.

Decision making is part of the human behaviour, an act of solving a problem that occurred within a particular problem space (Boland, 2008). Additionally, decision making is a critical process that takes place in every organization and quite often is related to managing and organization (Simon, 1977). Furthermore, it is something directly influences the organizations' performance and it is something that the organizations should build their structure around (Blenko et al., 2010). Decision making occurs right before taking any action, while that action is a direct consequence of the decision that has been made before (Simon, 1977; Witte et al., 1972; Mintzberg et al., 1976).

Human decision making includes processes from information gathering to developing alternatives for a certain problem (Witte et al., 1972). Similarly, Griffith et al. (2008) see decision making as an activity consisted of information gathering and information use. Decisions are a specific commitment, choice to engage into doing a certain action (Mintzberg et al., 1976). Simon (1977) categorized decisions as programmed and non-programmed depending on the way managers handle the problem they are solving. The programmed decisions are repetitive, represent a routine, can easily be solved and have a definite procedure (Simon, 1977). The non-programmed decisions on the other hand, are new, novel, unstructured, difficult to solve and there is no clear method to solve them (Simon, 1977).

Management activities are classified in three types, based on the types of decisions they are required to make: strategic planning, management control, and operational control (Anthony, 1965). Strategic planning is related to the activities of top level management about achieving the overall goals and missions of the organization in near and far future, so it often requires them to make predictions of the future. The management control focuses on the actions that middle level management makes about guiding the organization to the strategic goals. Lastly, the operational control focuses on first line managers and their concerns about the day-to-day performance of the organization. (Anthony, 1965).

Gorry and Morton (1971) came up with the terms "structured" and "unstructured" types of decisions which are conceptually related to Simon's classification of "programmed" and "non-programmed" decisions (Simon, 1977). In addition to that, Gorry and Morton (1971) introduced the term "semi-structured" decisions to address the need for having a category of decisions that is between the two extremes. Furthermore, Gorry and Morton (1971) created a framework for categorization of decisions over two dimensions: management activities classified by Anthony (1965) and classification of decisions previously introduced, which follows the ideas from Simon (1977).

Table 2.3 Categories of decisions and examples (Gorry and Morton, 1971; Courtney, 2001)

	Strategic Planning	Management Control	Operational Control
Unstructured	E- Commerce	Career paths	Grievances
Semi-structured	Forecasting	Budgeting	Assignments
Structured	Dividends	Purchasing	Billing

Decisions differ in their immunity to automation based on their type (Courtney, 2001). Decisions can be more easily automated when they are structured, meaning when the decision's parameters and alternatives are well known. For this type of decisions, a DSS can fundamentally change the nature of work in the organizations by delegating the decision to a DSS (Griffith et al., 2008). Having that done, the decision makers can focus more on the unstructured decisions where the parameters and alternatives are not complete. DSS should supplement the human decision making and not replacing the human factor (Griffith et al., 2008).

2.3 Theoretical frameworks

The selection of theoretical frameworks which we are going to discuss in this section was made in order to help us address our research question and provide us with theoretical foundation which we would use in order to answer it. Coming from our research question: "*What are the perceived effects of the use of predictive analytics on decision making in organizations?*" the most logical way to address it is to look for theoretical frameworks that analyze the decision-making process itself and various aspects of it in the context of organizations. Afterwards, we would use those frameworks to assess the influence, effects and perceived effects from the use of predictive analytics on decision making in organizations.

Regarding the decision making as a process composed of different phases, or sub-processes (Witte, 1972), a number of frameworks have been proposed by several researchers. Those frameworks break down decision-making process into phases ranging from three to eight (Mintzberg et al., 1976). Simon (1977) sees the decision-making process in organizations as being consisted of: intelligence, design and choice phase. Additionally, Dewey (1933) proposed a model of five phases: suggestion, intellectualization, development of hypotheses, reasoning or mental, and finally testing of the hypotheses. Furthermore, Leidner and Elam (1993) understand the decision making as a set of scanning, monitoring and communication activities.

Many researchers have investigated the effects of information technologies on decision making using different approaches and different frameworks. Some researchers studied the effects of information technologies on several dimensions of decision making. Raghunathan(1999) for instance, investigated the effects of decision support systems (DSS) on the quality of decisions based on the well-known input-process-output model employed in economics, systems analysis, and decision analysis as in

Figure 2.4.

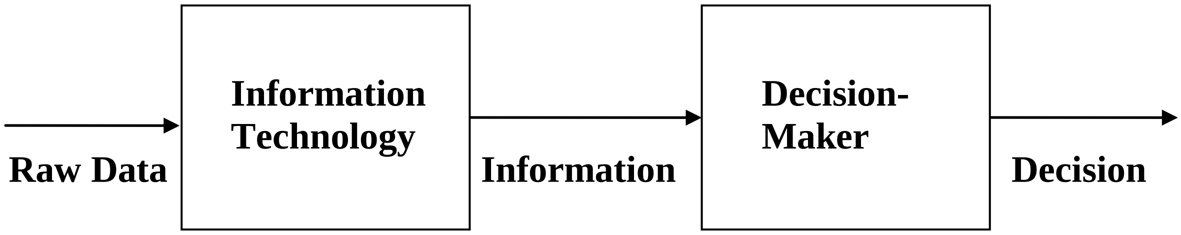

Figure 2.4 Input-process-output model (Raghunathan, 1999)

Other researchers studied the effects of a specific category of information systems on a particular perspective over decision making. For instance Mukhopadhyay and Cooper (1992) explored the impact of management information systems (MIS) on quality of the decisions from microeconomic production perspective by applying decision production theory. The input of this model is information provided by MIS while the output is a decision which is being made. The interaction can be evaluated by comparing the output with the expected output from the microeconomic perspective.

Furthermore, Bakos and Treacy (1986) built structural model for studying the effects of information technologies on organizational decision making, by categorizing the characteristics of the information technology. It was built on the consideration that studying the use of IT should be done by improving the quantity, quality, and efficiency of data collection storage, processing, and communications (Bakos and Treacy, 1986; Molloy and Schwenk, 1995). However, Molloy and Schwenk (1995) provided a modified version of Bakos and Treacy model, as shown in Table 2.4.

Table 2.4 Modified structural model (Molloy and Schwenk, 1995)

	Data access	**Processing**	**Communication**
Capacity	Breadth and depth of databases	Range and depth of system functions	Size of network
Quality	Appropriateness of data	Ease of use	Appropriateness of media
Speed & Efficiency	Cost of data management	Cost per transaction Cost per user	Cost per message Cost per user

In Table 2.5, according to the literature review that we did, we provide a summary of the theoretical models, approaches and the main focus areas when the models were applied in the context of exploring and analysing the effects of information technologies or information systems on decision making in organizations.

Table 2.5 Recent related Information Technology and Decision making literature

Authors	**Focus**	**Type of IT/IS**	**Theoretical approach**
Raghunathan (1999)	Impact of information quality and decision-maker quality on actual decision quality	DSS	Input-process-output model employed in economics. Cooper (1983)
Leidner and Elam (1995)	Impact of Executive Information Systems (EIS) on several organizational outcomes: Decision making speed, problem identification speed, information availability, involvement of subordinates in decision making	Executive Information Systems	Huber (1990)
Leidner and Elam (1993)	Effects of EIS on aspects decision making	Executive Information Systems	Huber (1990)
Mukhopadhyay and Cooper (1992)	Impact of Management Information Systems on Decisions	Management Information Systems	Microeconomic production theory
Molloy and Schwenk (1995)	Effects of IT on strategic decisions	Wide range of IT	Mintzberg, Raisinghani, and Theoret (1976) ; Bakos and Treacy (1986)
Dewett and Jones (2001)	Impact of IT on organizational characteristics: structure, size and learning and outcomes: organizationally efficiency and innovation	Wide range of IT	Various frameworks including Huber (1990)
Lawler and Elliot (1996)	Effect of IT in human resource management: problem solving accuracy and efficiency, confidence in use of ES, perceived ease of use, task Attitude	Expert system	Behavioural decision theory
Carter et al. (1994)	Effects of computer technology and decision structures in enhancing organizational performance.	Wide range of IT	Daft (1978) dual core approach.

Based on the literature review that we conducted, the most suitable theoretical frameworks to address our research question were Simon's model of the decision-making process in organizations (Simon, 1997) and Huber's theory of the effects of advanced information technologies on organizational design, intelligence and decision making (Huber 1990). To be more specific, we chose the famous Simon's model of decision-making process because it decomposes the decision making in organizations, breaks it down to 3 phases (Intelligence, Decision and Choice) and analyzes their characteristics. Since we want to analyze how the use of predictive analytics affects decision making in organizations, it is necessary to familiarize ourselves with each phase, to be able to address them individually and investigate how the use of predictive analytics affects them. In addition to that, Simon's model is widely adopted in IS literature and especially in the domain of DSS (Gorry and Morton, 1971; Keen, 1981; Choo, 1996; Courtney, 2001), which motivated us to use it for the purpose of examining the effects of predictive analytics on decision making.

Furthermore, we selected Huber's theory as it is most suitable in our context and can directly help us understand the perceived effects from the use of predictive analytics as an advanced information technology, on organizational intelligence and decision making. Huber's theory is one of the most influential frameworks in its domain (Te'eni, 2001) and includes a wide range of organizational characteristics as dependant variables which are affected by the use of IT as independent variable in relation with decision making in the organization (Huber, 1990; Dewett and Jones, 2001).

In this section, we will analyze both the Simon's model of decision-making process and Huber's theory of the effects of advanced information technologies on organizational design, intelligence and decision making.

2.3.1 Simon's model of the decision-making process

One of the most popular models that illustrate the decision making in organizations, which is widely used amongst IS researchers, especially in the areas of decision support systems (DSS) is the Simon's model of the decision-making process. Introduced in his book (Simon, 1977), the model recognizes three phases of the decision-making processes in the organizations, which are the intelligence, the design and the choice phase. "Generally speaking, intelligence activity precedes design, and design precedes choice" (Simon, 1977, p. 3), while the whole process is not a simple sequence, but rather very complex (Figure 2.5), as each phase can be a complex decision-making process itself (Simon, 1977).

Simon in his book describes the three phases of the decision-making process in simple words as providing answers to the questions (Simon, 1977, p. 3):

"What is the problem?"
"What are the alternatives?"
"Which alternative is the best?"

To present a better understanding of the context, Turban et al. (2011) make a relation connecting Simon's model for the decision-making process and the model from Tuckman (1965) about group decision making which consist of the phases forming, storming, norming and performing. Based on the tasks and processes that are being conducted in each phase, they connect the storming phase with intelligence phase, norming phase with the design phase and performing with phase with the choice phase from Simon's model (Simon, 1997).

Next in this section, we will elaborate on each of the three phases of the decision-making process, individually, according to Simon (1997).

Intelligence phase

The intelligence phase is all about finding the occasions over which a decision should be made (Simon, 1997). "The major role of the intelligence stage is to identify the problem and collect relevant information" (Turban et al., 2011, p. 144) which would be used later in the next stages of the decision-making process. The activities that are associated with the intelligence phase are indentifying problems (opportunities), collecting and sharing information and identifying decision criteria (Turban et al., 2011).

Once the indicators or symptoms about a certain event are recognized and known, then the problem or the opportunity can be defined and assessed if it is important or urgent, so the decision maker (or the decision making team) is able to proceed to the next phase of the decision-making process (Turban et al, 2011).

Design phase

After the problem has been identified, the next step in the decision-making process is to develop and evaluate multiple scenarios which would be considered as available solutions to the problem (Simon, 1997; Turban et al., 2011). Simon (1997) looks at the design phase as the step in the decision-making process where the possible courses of action are being found. The tasks that the design phase is connected to, are the following: finding alternatives, evaluating alternatives, comparing alternatives and prioritizing alternatives (Turban et al., 2011).

Choice phase

Making a choice "requires some analysis, deliberation, discussion, voting and negotiation" (Turban et al., 2011, p. 146). Simon (1997) relates the choice phase to selecting a particular course of action out of the pool of available courses, which were created in the previous, design phase. The actions that the choice phase is related with are listed by Turban et al. (2011) and are doing a sensitivity analysis and making selection of an alternative which is considered to be the output of the decision-making process, or the decision itself that was brought by the decision makers.

An illustration of the decision-making process (Simon, 1977; Turban et al., 2011) is presented on Figure 2.5.

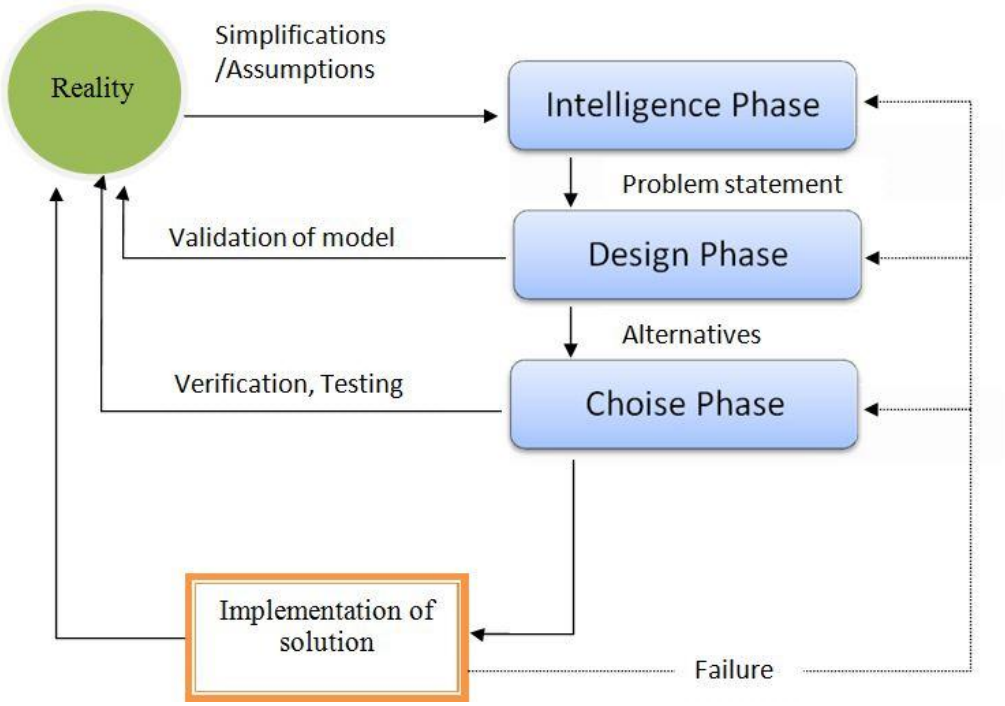

Figure 2.5 Model of the decision-making process (Simon, 1977)

2.3.2 Huber's theory of the effects of advanced information technologies on organizational design, intelligence and decision making

Huber (1990) introduces a theory about the effects of computer-assisted communication and decision-aiding technologies (advanced information technologies) on organizational design, intelligence and decision making, which is later to be widely used and referred to by many information systems researchers. When discussing about advanced information technologies, what the author refers to is technologies that include transmitting, manipulating, analyzing or exploiting information, where digital processing of information is a necessity for user's communication or decision task and in fact represents a significant aid and assistance to the completion of the communication or decision task. Having said that and taking into consideration the previous discussion about predictive analytics as a mean for decision support, we can consider predictive analytics as an advanced information technology in the context of Huber's theory.

The motivation that Huber (1990) had for creating of this theory is the following: (1) there was a need to reinvestigate and revise components of organization theory; (2) it was time for theory development to evolve forward by creating a theory about the effects from advanced information technologies on organizations; (3) help researchers working in the areas of organizational science, communication and information systems so that they all become aware of the importance of the work they all do, therefore their work becomes better integrated and better theories are developed; and (4), considering from the pervasive nature that advanced information technologies have in organizations and combining it with their recent appearance and fast changes, their users and advisors will not have experience to help them facilitate the impact of these technologies on the organizations, therefore a theory would be of great importance.

Huber (1990) selected 13 dependant variables and described the relations among them with 14 propositions. The dependant variables are selected from two pools. The first pool is concerned with the characteristics of organizational intelligence and decision making, while the second pool is about the aspects of organizational design that are related with intelligence and decision making. Considering the large size of both pools, Huber (1990) selected only the variables which are highly affected by advanced information technologies in the organizations, attract higher interests from both researchers and practitioners and finally the ones whose divergence increased with the arrival of advanced information technologies. The independent variable included in the theory, on the other hand, is the use of advanced communication and decision-aiding technologies (advanced information technologies).

The propositions and the variables in the theory are categorized in four groups which we will analyze next. The first three groups are concerned with organization structure and designs, as components that influence organizational decision making. The fourth group is about the direct effects of advanced information technologies on organizational intelligence and decision making. (Huber, 1990).

Effect of Advanced IT at subunit level

The focus of this category is on the various effects from the use of advanced information technologies that are created at a subunit organizational level and have an influence on the organizational intelligence and decision making. The addressed variables in this category are:

participation in decision making, size and heterogeneity of decision units and frequency and duration of meetings.

The participation in decision making is assessed by the number and variety of people that participate as information sources in the decision-making process (Huber, 1990). Additionally, the participation in decision making is defined as the extent to which the management allows employees' input into decisions and it is ranging from alternative analysis to joint decision making (Cooper and Wood, 1974; Miller and Monge, 1986), or from consulting employees on work related issues to employees taking decision on their behalf (Probst, 2005). Huber (1990) argues that advanced information technologies reduce both time and effort spent by individuals in organization to communicate, consequently more people are able to share information thus serving as source of information themselves. That information later on is being used as a base for making decisions in the organization.

The next variable addresses the size and structure of decision units where decision unit is an individual or a group of individuals whose role requires selecting course of action for the organization and are being held responsible for that (Duncan, 1973; Duncan, 1974; Huber, 1990). The structure of the decision units refers to the background and experience of its members (Huber, 1990). Theory suggests that decision units will be consisted of less people and will be more homogenous as a result for using advanced information technologies since they are provided with more information compared to traditional ways where advanced information technologies are not used (Huber, 1990).

The last variable within this category examines the frequency and duration of meetings about decision making in the organizations. Meetings are ways for the employees in a company to directly take part in decision making and information sharing (Tracy and Dimock, 2004; Yoerger et al., 2015). Even though meetings are used to make the decision-making process go faster in the organizations, they reserve a significant portion of decision makers' time often because lack of information (Huber, 1990). Theory suggests that the use of advanced information technologies can speed up the meetings and reduce the need for subsequent meetings, by making information more available and even provide new information which enables decision makers to run analysis and make decisions faster (Huber, 1990).

Effects of advanced IT at the organizational level

The second group of propositions and variables is about the effects generated at the level of the whole organization by the use of advanced information technologies and as such, they influence the organizational decision making. This category groups the following variables: centralization of decision making, number of organizational levels involved in authorization and number of nodes in the information-processing network.

Carter et al. (1994) see centralization as the extent to which authority is concentrated in the top levels of organization hierarchy while decentralization is the extent to which that authority is allowed down in the hierarchy. Decentralization of the decision making refers to the ability of several decision makers (individuals or groups) to make decisions instead of one (Tsitsiklis, 1984), while centralization has the opposite meaning. Accordingly, the variable of centralization of decision making assesses the level of centralization in the decision-making process of an organization. Theory suggests that the availability of advanced information technologies in different levels of organization leads to a more uniform distribution of the probability that particular organizational level makes a decision (Huber, 1990). Additionally, with the use of advanced information technologies decisions are made in wider range of organizational levels with a satisfactory degree of decision quality and timeliness for the organization (Huber, 1990).

The number of levels involved in authorizing actions directly affects the decision-making process, making it slower as the number of levels increases (Huber, 1990; Shumway et al., 1975). Organizations usually tend to have many hierarchical levels since each hierarchical level has more knowledge about their domain, making them more qualified to take the right decision (Huber, 1990). Theory suggests that the usage of advanced information technologies would make information more available and consequently reduce the number of organizational levels involved in authorizing decisions (Huber, 1990).

The last variable in this category as the name suggests, addresses the number of nodes in the information-processing network in the organizations. The information-processing network dealing with decision situations usually consists of many nodes (units). Frequently outer nodes (sensor nodes) sense, gather the information, change or simply direct it to another node which will process it and send it to another information processing unit, for instance, closer to the final decision making unit or user (Huber, 1990). The theory proposes that advanced information technologies stimulate reduction of the intermediate units in the information-processing network (Huber, 1990).

Effects on organizational memory

The third group of propositions and variables is concerned with the effects from the use of advanced information technologies on organizational memory, that directly influence the organizational information, knowledge and decision making. Organizational memory is defined as “stored information from an organization's history that can be brought to bear on present decisions” (Walsh and Ungson, 1991, p.61). In addition to that, organizational memory involves encoding the information in appropriate representation so it can be used and interpreted later in the organization (Stein, 1995).

The first variable measures the level development and use of data bases in relation with the use of advanced information technologies (Huber, 1990). The second variable on the other hand measures the level of development and use of in-house expert systems as components of organizational memory, with relation to the existing procedures for development and use of the expert systems in the organizations and the use of advanced information technologies (Huber, 1990).

Huber (1990) suggests that increased availability of advanced information technologies and more user-friendly procedures stimulates the development of organizational memory components.

Effects on organizational intelligence and decision making

The last group is concerned with the direct effect on the decision-making process, as well as its output, a decision. The variables in this category are: effectiveness of environmental scanning, quality and timeliness of organizational intelligence, quality of decisions and speed of decision making.

The effectiveness of environmental scanning is measured through the speed and accuracy of identification of problems and opportunities for the organization (Huber, 1990). The use of advanced information technologies enables faster and more accurate environmental scanning according to theory (Huber, 1990).

Organizational intelligence is defined as the output from acquiring, processing and interpreting information foreign to the organization, and also the input in the decision-making process (March, 1999; Huber, 1990; Sammon et al., 1984). The quality of the organizational intelligence is assessed through accuracy and comprehensiveness of the organizational intelligence (Huber, 1990). In addition to that, the use of advance information technologies improves the quality and timeliness of organizational intelligence (Huber, 1990).

The quality of a decision is a relation between the selected alternative by the decision makers and the correct or best alternative (Ge and Helfert, 2013; Raghunathan, 1999) and is also directly dependent on the accuracy, availability and coverage of the information that an organization has (Mukhopadhyay and Cooper, 1992). In addition to that, the quality of the decisions is a consequence of both the organizational intelligence and the quality of decision-making process (Huber, 1990). Theory states that the quality of decisions is enhanced by using advanced information technologies, mainly due to increase of the quality of information processing and sharing (Huber, 1990).

Lastly, the speed of decision making represents the time from the point when decision makers realize the need for a decision to be made, to the point when the decision is actually made (Leidner and Elam, 1993). The speed of decision making is assessed through the time needed for a decision to be made and actions to be authorized accordingly (Huber, 1990). Furthermore, advanced information technologies can aid decision makers to analyse data quickly and also decrease the time required to authorize proposed actions and make decisions within the organization (Huber, 1990).

Finally, in Table 2.6 we provide a summary of the literature review we did, analysing in what context was Huber's theory used in previous IS research, what has been done and what are the findings. We present this information to give the reader a more detailed perspective of the applicability of the Huber's theory.

Table 2.6 Related IS research done using Huber's theory

Authors	Focus	How Huber's theory is used	Findings
Leidner and Elam (1993)	Effects of Executive Information Systems (EIS) use on aspects of decision-making process.	Use Huber variables and interpretation of those variables used in his theory to measure some variables like speed of decisions.	Came up with six hypotheses which examine the effect of EIS use on decision making at the individual level. Those hypotheses explain the relation of EIS use with problem identification speed, decision making speed, and the extent of analysis in decision making.
Leidner and Elam (1995)	Impact of Executive Information Systems (EIS) on several organ-	Developing eight hypotheses explaining the impact of EIS on organization based on proposi-	Eight test hypotheses which are based on Huber. However they add enhancements on some of the

	izational outcomes: - decision making speed - problem identification speed - information availability - involvement of subordinates in decision making	tions from Huber's theory.	Huber's findings. That helps Huber's theory to better explain the relation between EIS use and improved organizational intelligence and decision making outcomes.
Dewett and Jones (2001)	Impact of IT on organizational characteristics: structure, size and learning and outcomes (organizational efficiency and innovation)	Extending and updating Huber's theory.	Extends and updates Huber's theory to better understanding of how IT will rewrite various portions of management theory. By extending Huber theory in: - focus on the two strategic outcomes of efficiency and innovation. -Organizational functioning. -Examine IT as a moderator of the relationship between organizational characteristics and several organizational outcomes.
Zhang et al. (2006)	Study domino effect by the use of Radio frequency identification (RFID) as an advanced information technology on an organization's IT infrastructure, business intelligence, and decision making.	The study based on Huber theory to examine effect of RFID by proposing a series of propositions which based on Huber propositions.	Conceptual research framework of empirically tested hypotheses that illustrates the effect of RFID technology usage.
Fiedler et al. (1996)	Relation information technology (IT) and organizational structures. It focus on IT structure based on the degree of: - Centralization of computer processing - Capability to support communications - Ability to share resources	Develop further one of the propositions based on Huber theory findings about centralization and decentralization propositions.	This study empirically develops a taxonomy that has implications for matching information technology and organizational structures. The four IT structures are identified: - centralized - decentralized - centralized cooperative - distributed cooperative computing
Carter et al. (1994)	Computer technology and decision structures' role in enhancing organizational performance in the technical and administrative core of the organization.	The study investigated some of those benefits based on Huber's theory key benefits of IT on decision making. Mainly decision making speed, and decentralization.	Overall organizational performance is affected by computer usage and decision-making process in subunit levels. Also this change does not need to arise from the same conditions in different cores of the organization.
Park (2006)	Examine effects of a data warehousing on decision quality and performance.	The study showed that Huber's theory is valid in the context of data warehouse and DSS.	The adoption and use of a fully capable data warehouse has improved DSS users' decision performance.
Calhoun et al. (2002)	The use of nonspecific applications of information technology for organizational decision mak-	Depend on Huber theory to identify decision attributes which is related to IT usage in order to	Decision makers perceive the impact of IT upon decision factors which is defined based on Huber. Also non-specific use of

	ing.	use them in questionnaire.	IT is more free of culture rather than the use of specific application like EIS.

2.4 Our research framework

In this chapter we provided a theoretical foundation which is needed in order to be able to understand and answer our research question. More specifically, we explained the context and importance of predictive analytics starting from business intelligence and narrowing it down to business analytics and predictive analytics. In addition to that, we discussed what decision making means according to scientific literature and analyzed theoretical frameworks which we will use in order to address our research question.

We are going to answer our research question by using Simon's model of the decision-making process (Simon, 1977) and assessing the influence from predictive analytics on each stage of the process. Having decomposed the decision-making process like that, we would be able to generate knowledge about the effects of predictive analytics on decision making in organizations.

In addition to that, we are going to test the propositions of Huber's theory (Huber, 1990) in the context of examining the effect from the use of predictive analytics as advanced information technology on organizational design, intelligence and decision making. We will do that by investigating whether the use of predictive analytics generates the same effects in line with each proposition of Huber's theory. The variables used in the propositions which we are going to assess are listed in Table 2.7, categorized in line with the theory.

Table 2.7 Categorization of the addressed variables in line with Huber's theory

Category	Variable	Used in proposition number
Effects at sub-unit level	Participation in decision making	1
	Size and heterogeneity of decision units	2
	Frequency and duration of meetings	3
Effects at organizational level	Centralization of decision making	4, 5
	Number of organizational levels involved in authorization	6
	Number of nodes in the information-processing network	7
Effects at organizational memory	Development and use of computer-resident data bases	8
	Development and use of computer-resident in-house expert systems	9
Effects at organ-	Effectiveness of environmental scanning	10

izational intelligence and decision making	Quality and timeliness of organizational intelligence	11
	Quality of decisions	12
	Speed of decision making	13, 14

Finally, we present a list of the propositions that Huber's theory suggests (Huber, 1990) in the context of assessing the effects of predictive analytics as an advanced information technology on organizational design, intelligence and decision making (Table 2.8). Additionally, we have to state that testing proposition 5 would require investigation on a larger population of organizations which make same types of decisions so that generalization would be possible. Our study will target types of organizations that do not necessarily make the same types of decisions, to ensure generalizability of the findings regarding the test of the other propositions. Therefore, proposition 5 would be out of scope in our study. Furthermore, after the presentation of the propositions in our context of predictive analytics, those propositions according to Huber's theory (Huber, 1990) can be grouped in 4 groups (concepts) as visualized in Figure 2.6.

Table 2.8 Propositions from Huber's theory modified in the context of predictive analytics

No.	Proposition
1	Use of predictive analytics leads to a larger number and variety of people participating as information sources in the making of a decision.
2	Use of predictive analytics leads to decreases in the number and variety of members comprising the traditional face-to-face decision unit.
3	Use of predictive analytics results in less of the organization's time being absorbed by decision-related meetings.
4	For a highly centralized organization, use of predictive analytics leads to more decentralization.
5	For a population of organizations, broadened use of predictive analytics leads to a greater variation across organizations in the levels at which a particular type of decision is made.
6	Use of predictive analytics reduces the number of organizational levels involved in authorizing proposed organizational actions.
7	Use of predictive analytics leads to fewer intermediate human nodes within the organizational information processing network.
8	Availability of predictive analytics leads to more frequent development and use of computer-resident data bases as components of organizational memories.
9	Availability of more robust and user-friendly procedures for constructing expert systems leads to more frequent development and use of in-house expert systems as components of organizational memories.
10	Use of predictive analytics leads to more rapid and more accurate identification of problems and opportunities.
11	Use of predictive analytics leads to organizational intelligence that is more accurate, comprehensive, timely, and available.
12	Use of predictive analytics leads to higher quality decisions.
13	Use of predictive analytics reduces the time required to authorize proposed organizational actions.
14	Use of predictive analytics reduces the time required to make decisions.

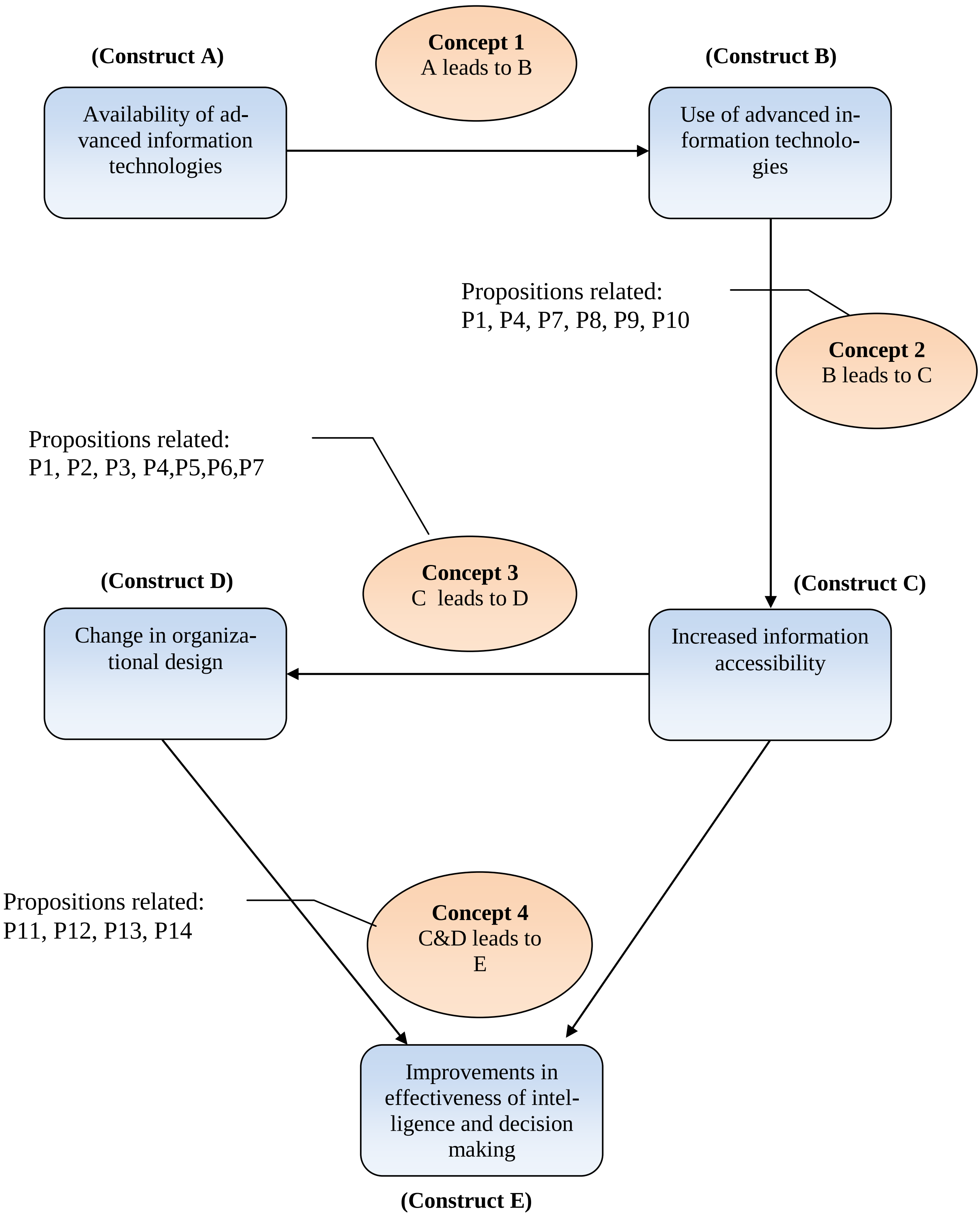

Figure 2.6 Concepts of Huber's theory (Huber, 1990)

3 Research Method

The objective of our study is to examine the perceived effects of the use of predictive analytics on decision making in organizations. So far we introduced our problem area, research question and purpose and also outlined the relevant literature in the context of our study. We explained the motivation of the selection of our theoretical framework as a mean to provide answers to our research question. In this chapter we discuss the selection of our research method, data collection and data analysis approach which we incorporate in our study, in accordance with relevant methodological literature. Furthermore, we make a discussion of the critical aspects of our research approach in terms of validity, reliability and ethical concerns.

3.1 Method Choice

The research question is considered to be the "fundamental cornerstone" around which the whole research revolves and evolves, the frame in which the whole research and representation can be put (Recker, 2013). Therefore, the research question is the one that dictates the choice of the research method.

We decided to follow a qualitative approach in order to get deeper understanding of our study problem because the qualitative research is considered to be most suitable for "research where a phenomenon is not yet fully understood, not well researched, or still emerging" (Recker, 2013, p. 88). In addition to that, it would not be suitable to do our research regarding the use of predictive analytics in organizations by adopting quantitative approaches and surveys. Furthermore, one key characteristic that the interviews as a method have, unlike surveys, is that respondents could be asked follow-up questions, questions for clarification and questions for getting a greater understanding of the research phenomenon (Miles and Huberman, 1984; Bhattacherjee, 2012).

We chose to conduct semi-structured interviews as a way to collect data as we believe that they enable us to better investigate how the decision making in organizations is affected by the use of predictive analytics. In addition to that, these types of interviews would provide means for the questions and the answers to be more dynamic, thus allowing us to deliver findings and obtain insights that maybe we did not thought of, when constructing the interview guide. We find this flexibility to be advantageous in the case of our research problem and therefore consider semi-structured interviews to be superior to fully structured interviews for our cause.

3.2 Data collection

The qualitative approach in our study allows us to choose the most relevant sources of information that are of interest (purpose sampling in contrast to random sampling), build cases around them and analyze them in order to assess a certain phenomenon (Recker, 2013; Bhattacherjee, 2012). "With qualitative data, one can preserve chronological flow, assess logical causality, and derive fruitful explanations" (Miles and Huberman, 1984, p. 23). Following the chosen research method, as described in the previous section, we collected empirical data by interviewing decision makers who belong mainly in the upper level management in their organizations and actively use, have used predictive analytics and/or manage subordinates who use predictive analytics and feed them with information that supports the decision making. Those individuals have the knowledge and experience in our area of interest and are to be considered as valuable sources of information for our research. In addition to that, in the next chapter we present the data we collected from various reports, articles and journals to be able to provide rich information about the analyzed cases and the contexts accordingly.

Furthermore, before making the interviews in first place, we were aware of the potential strategic importance of the predictive analytics as a resource in the companies, so that the disclosure of some valuable information could endanger their businesses. Most certainly, that is not what we are trying to achieve, which is why we provided those companies with the opportunity to stay anonymous in the interview process upon request, with us not disclosing any names of other companies, locations etc. That type of data is not adding any value to our study and purpose.

The collection of empirical data for our study is based on semi-structured interviews which suggest that a formal structure of questions is not completely followed. That provided us as researchers with an opportunity to come up with new questions during the interviews whenever they were necessary as well as to ask for further details or clarifications, in order to get a bigger understanding over the topics discussed. In addition to that, semi-structured interviews give flexibility not only to the interviewer but to the interviewee as well, making them more comfortable during the process (Recker, 2013).

Some of the benefits over other techniques that semi-structured interviews carry with them are that they are less intrusive to the people that are being interviewed, empowering two-way communication; they might be used to confirm already known matters as well as to create an opportunity to learn new matters and the reasons for their occurrence; with semi-structured interviews more sensitive issues to the interviewees can be approached and discuss in a more convenient and easy way (Recker, 2013). Having all that in mind, we went on to develop our interview guide.

3.2.1 Development of the interview guide

The interview guide provides a framework that guides the process of the semi-structured interviews in our research. Interview guide is generally a list of predefined questions that would be asked within the scope of problem area that will guide the conversation with the interviewee (Recker, 2013). In the design of our interview guide we followed recommendations from Myers and Newman (2007), like for instance, we ensured to prepare proper introduction and closure for the interview. In addition to that, the questions sustain the flexibility by letting the conversation lead the questions. Further, our open-end questions give the chance to the respondent to express their opinion on some points.

The interview guide we developed in accordance with our theoretical framework presented in Chapter 2.4 and it consists of six sections which are: introduction, the effects from the use of predictive analytics on organizational intelligence and decision making, the effects from use of predictive analytics at subunit level, the effects from the use of predictive analytics at organizational level, the effects from the use of predictive analytics on organizational memory and a debriefing section.

In the *first section* we ask questions to help us get to know the interviewee better, their role in the company, the decisions they are required to make as well as their relationship with predictive analytics. With the questions in the *second section* we assess how predictive analytics influences directly on decision making, decision authorization in organizations and the organizational intelligence, following Huber's theory (Huber, 1990). In addition to that, in this section we introduce questions which answers should help us analyze the effects of predictive analytics on the decision-making process in organizations according to Simon's model (Simon, 1977). That means that we address each of the three phases of the decision-making process that Simon identifies: intelligence, design and choice, separately. The *third section* of the interview guide is related to questions that assess the effects from the use of predictive analytics on the organizational memory, as a vital component and factor that directly influences decision making (Huber, 1990). The *fourth part* of our interview guide focuses on the effects that are being created at the subunit level in the organization and yet affect various aspects on decision making according to Huber (1990) like the size and structure of decision units, participation in decision making and time consumed on meetings for making a decision. The *fifth part* of our interview guide on the other hand, is about the effects that appear at the level of the whole organization and influence decision making according to Huber (1990). The segments that are being addressed there are the centralization of decision making, number of organizational levels involved in authorization and number of nodes in the information processing network, and what we do there is inspect the effect of the use of predictive analytics on all those segments, in line with the Huber's theory (Huber, 1990).

The last section of our interview guide has the purpose to make a closure of the interview, ask for general opinion over predictive analytics and make sure that the interviewee has fully stated his opinions without omitting any segments.

The structure of our interview guide can be found below, while the full structure including all of the questions can be accessed in Appendix A.

Introduction

Effects on organizational intelligence and decision making

Environmental scanning and organizational intelligence

Decision making and decision authorization

Effects on the Intelligence phase

Effects on the Design phase

Effects on Choice phase

Effects from the use of predictive analytics on organizational memory

Effect from the use of predictive analytics at subunit level

Participation in decision making

Size and structure of the decision units

Frequency and duration of meetings

Effect from the use of predictive analytics at organizational level

Centralization of decision making

Number of organizational levels involved in authorization

Number of nodes in the information processing network

Debriefing

We believe that this structure of the interview guide will help us to obtain the right empirical data which would be analysed in order provide answers our research question.

3.2.2 Interviewing

The companies that we target for the interviews are retailers since they are one of the biggest incorporators of data analytics in their way of working and especially for our purpose, predictive analytics (Davenport, 2006). Therefore they are familiar with the areas that we want to investigate in and they are able to provide rich data and high quality answers to our questions. Additional requirement is that their IT maturity, development and experience to be on a high level so that they actively use predictive analytics as a mean to support their decision making. Furthermore, we focus on organizations doing retail as a general domain (meaning they have certain products or services which they offer and sell to individuals), without having interest in particular domain within the industry, like for instance food, clothes, technical products (phones, laptops, TVs, etc). The location where these companies are headquartered in also does not add any value to our study, which opens an increased flexibility for us as interviewers in terms of having the freedom of contacting more companies in order to find collaborators.

In the process of looking for candidates to do the interviews with, we must mention that we had to contact multiple companies via phone calls, e-mails and LinkedIn in order to find the ones that would like to work with us. The predictive analytics is considered as a unique resource for the companies in general. Hence, informants from companies are not feeling comfortable discussing these matters with outsiders to the companies. In order to address their needs and make them feel more comfortable for the interviews, we provided them with the opportunity to keep them anonymous upon request without disclosing details about the companies, the interviewees themselves, their systems, their clients and every other data that they would like to keep private and does not add any value to our research.

Interviews can be individual and group (Mayers and Newman, 2007), depending on the number of interviewees they were conducted with. We made six interviews in total in six different companies and only one interview was conducted with two informants upon their request, since they believed that together they would provide richer answers. Five out of those six companies we did an interview in, act as retailers and are direct users of predictive analytics which supports the making of decisions about their business. Those five companies directly experience the effects from the use of predictive analytics on decision making and we used the information from them to build individual cases and analyze them as empirical foundation of our study.

The companies we had an interview with were T-Mobile, headquartered in Germany, One (Telekom Slovenia Group), headquartered in Slovenia, IKEA Sweden and Semos which is an IT consultancy company in Macedonia. Two companies preferred keeping their names anonymous and here are basic details about them: DBank – one of the biggest banks in Macedonia which is a part of a big bank headquartered in Greece; C-Retail is a retailer that operates in the Balkans and is headquartered in Macedonia.

The sixth company, Semos, is an IT consultancy also headquartered in Macedonia, which works with implementation and maintenance of predictive analytics systems in retailing companies and also makes trainings for the employees to use them. The consultant we interviewed there provided us with general insights about the experience of their multiple customers, which is valuable information that should help us improve the generalization of our findings.

All of the interviews were made face-to-face since that approach is more comfortable both for the interviewees and us as researchers, avoiding any possible technical inconveniences and barriers that could occur via teleconferencing using Skype for instance. All of the interviews were done in English except for the one with C-Retail where the interviewee requested specifically to have the interview in Macedonian language for increased convenience. Short summary of the details regarding the interviews we conducted can be found in Table 3.1.

Table 3.1 Summary of the conducted interviews

Company	Interviewee	Interview		
		Duration	**Date**	**Language**
T-Mobile	Director of Marketing Intelligence and Market Planning	75 min	April 21, 2015	EN
One (Telekom Slovenia Group)	Senior Analytics Specialist	60 min	April 24, 2015	EN
DBank	Chief Retail Officer	90 min	April 28, 2015	EN
	Department Manager of Card-products			
C-Retail	Regional Sales Manager	60 min	April 22, 2015	MK
IKEA	Visual Merchandise leader	60 min	May 15, 2015	EN
Semos	Predictive analytics consultant	45 min	April 24, 2015	EN

Before making the interviews, we had understood the complexity and importance of the interviewer’s role and followed the recommendations from Bhattacherjee (2012) regarding the interview process: to prepare good for the interview in advance, to locate and enlist cooperation of respondents, motivate the interviewees to provide useful and high-quality responses, clarify any confusion or concerns in case they arise for the interviewees, and also observe the quality of the responses.

The respondents had no access to the interview questions before the interview was conducted, in order to avoid any potential biases in the answers. They were only introduced beforehand to the topics that we want to discuss about during the interviews, so that we are all sure that they are the right people that are able to make the discussions in first place. All the interviews were conducted in the offices of the companies, in person. During the interviews, we relied on the interview guide in order to make sure that we cover all of the questions and topics that are required. However, we were adapting to the flow of the conversation by not always following the same order of questions. We also made sure that we do not ask questions to which the respondent already answered when they were answering another related question and gave an extensive and well elaborated response. That way we avoided same thoughts and opinions said by the interviewees to be doubled.

In cases when the responses of the interviewees were considered to be brief, we used some of the probing techniques discussed by Bhattacherjee (2012): the silent probe of pausing and waiting, encouragement of the respondent to motivate for more detailed answer, direct asking for further elaboration and reflection of what has been previously said by the interviewee in order to get response in greater detail.

3.3 Data analysis

“The emphasis in qualitative analysis is “sense making” or understanding a phenomenon, rather than predicting or explaining” (Bhattacherjee, 2012, p. 113). Unlike quantitative research where data collection and data analysis are completely separate processes, that is not the case with qualitative research where these processes quite frequently are interconnected and dependent on each other (Recker, 2013). Additionally, the analysis of quantitative data is driven by statistics and mostly does not depend on the researcher, while the analysis of qualitative data on the other hand highly relies on the researchers’ analytic skills and ability to understand and analyze the context in which the data has been collected (Bhattacherjee, 2012).

Analyzing qualitative data “involves summarizing the mass of data collected and presenting the results in a way that communicates the most important features” (Hancock et al., 1998, p. 24). The most important characteristic of the data analysis which is done in qualitative research is that there is very big amount of data to be analyzed by the researcher who usually in first place has no knowledge of which part of that data is considered to be relevant or not in the results at the end, nor the reasons about it (Recker, 2013).

The thinking about how to analyze the data should not start before knowing the subject of the interview and the purpose of the interview (Kvale, 1996). Hence we clearly set the subject investigated as well as the purpose we are aiming to do with our interviews. As suggested by Kvale (1996), it would be too late to think about the method of analysis after conducting the interviews. So, after developing our interview guide we had comprehensive idea on the method of analysis for the data of our interviews.

Many techniques exist for analyzing data from conducted qualitative research, while among the most popular are (Recker, 2013): coding, memoing, critical incidents, content analysis and discourse analysis. We conducted the data analysis by first converting the interviews into text through transcription, and then we went through the coding phase in order to reduce the amount of data and identify relevant data, so that we are finally able to focus on analysis of the data from the coding phase.

3.3.1 Interview transcription

The transcription, as part of the data analysis, is the process of preparing the interview material for the next analysing phase by converting the audio recording into text (Kvale and Brinkmann, 2009). In our study all the interviews were conducted in a face-to-face form. We recorded the interview using smart phone applications that records the audio in a high quality. We started transcription right after each interview in order to be able to remember the impressions which we had during the interview itself and reflect it to the related transcript. Further, this way of transcribing will give us chance to gain better understanding of the interviews. Taking the fact that we are two members in this thesis, we decided that the transcript for each interview should be mainly done by the member who runs the interview. In order to improve the quality of the transcripts, transcripts will be cross-checked by the other member (Table 3.2). The high quality of the interview allow us to perform the transcription easily word-by-word and as well as for the cross-checking. After the transcribing was finished we sent the transcripts for the interviewee for their review and comments as suggested by Kvale and Brinkmann (2009).

Table 3.2 Summary of the transcribing process

Interviewed done at	Transcript number	Transcribed by	Checked by
T-Mobile	Transcript 1	Bojan Najdenov	Fadi Makhoul
One (Telekom Slovenia Group)	Transcript 2	Bojan Najdenov	Fadi Makhoul
DBank	Transcript 3	Bojan Najdenov	Fadi Makhoul
C-Retail	Transcript 4	Fadi Makhoul	Bojan Najdenov
IKEA	Transcript 5	Fadi Makhoul	Bojan Najdenov
Semos	Transcript 6	Bojan Najdenov	Fadi Makhoul

3.3.2 Coding and analyzing

Analysing qualitative data understands analysing a big portion of textual data (Bhattacherjee, 2012) which volume we needed to reduce in order to be able to draw conclusions out of it. Our approach in data analysis is based on Miles and Huberman (1984) analysis of qualitative data which is considered as flow of three concurrent activities: data reduction, data display, and conclusion drawing and verification. It is important to have in mind that all those phases are not taking place in separate manner. Following that we performed the data reduction by selecting the sentences and focusing on it and also by summarizing some others. The second phase is the display phase which mainly assembles and presents the information in a way that assists the next phase of making conclusions. The third phase of the analysis is drawing conclusion based on the information display.

The process of coding implies applying codes to a portion of text, which should lead to presentation of the data in a digestible way (Bhattacherjee, 2012). The coding scheme that we applied in our analysis was drown out of the themes we discussed in Chapter 2.4: intelligence phase, design phase, choice phase, effect at subunit level, effect at organizational level, effects on organizational memory, effects on organizational intelligence and decision making. In addition to that, we added an extra code concerning the interviewee's profile.

3.4 Critical reflections

3.4.1 Validity

Validity generally refers to the integrity of the methods applied in research and the precision of the conclusions which are drawn based on the data (Long and Johnson 2000). Validity can be broken down into different types such as internal and external validity.

To achieve internal validity in our research we worked on establishing credibility as suggested by Recker (2013). The research transcripts were sent back to interviewees for approval so they make sure that we correctly rendered their interviews. This is called by Seale (1999) "member checks" which gives credibility to the interviews by allowing respondents to review their transcripts and approve the way interviewers have represented them.

Moreover, we followed the general guidelines of qualitative interviews by Myers and Newman (2007) to achieve the quality of our interviews and worked on situating the researcher as an actor. We asked questions that help the reader to understand the background of the respondent and consequently help readers to assess our findings. Also the flexibility in our semi-structured interviews allowed us to construct subsequent questions, should the need for clarification arise.

External validity or generalizability refers to whether our research findings can be generalized to other population, domains or contexts (Bhattacherjee, 2012). We attempted to improve our external validity by providing rich and detailed descriptions where ever applicable so the reader will be able to judge our level of transparency where we can extend our findings to other domain.

3.4.2 Reliability

Reliability of the research is about getting pretty much the same observations and interpretations if the operation of study would be carried out again with the same settings (Bhattacherjee, 2012). It is often hard to apply rigor in qualitative research since qualitative methods are more subjective and dependant on the researcher own interpretation. In addition is has issues with generalizing the results of the study on another cases or domains (Recker, 2013).

However, there are means to ensure and demonstrate reliability in qualitative research. Guidelines exist to be applied in order to deal with subjective and interpretative nature of qualitative methods (Recker, 2013). Throughout our thesis we attempted to achieve high reliability by increasing transparency through clearly defining and describing our subject and purpose and research approach. We aimed to concern the subject and purpose of our interviews beforehand (Kvale, 1996). In addition, we attempted to achieve inter-observer reliability through conducting multiple observation and interpretation of data by the two members of the thesis (Recker, 2013). We avoided unreliable observation sources as recommended by (Bhattacherjee, 2012) by clearly building our interview questions and ensure forming them in a way that they not misinterpreted by some interviewee. Also we carefully selected our interviewees who are familiar with the topics and terms that we use in our study so they will fully understand our problem area.

3.4.3 Ethical issues

It is important to have in mind that many ethical issues may occur in each stage of scientific research. The ethical issues arise in social research are due to the complexity of studying private lives and trying to project it to the public account (Brinkmann and Kvale, 2005). As part of improving the quality of our research we attempt to avoid ethical issues by following the guidelines from Brinkmann and Kvale (2005).

Before each interview we provided the participant with general theme of our interview guide to present our purpose, intension and method of the interview. That way the interviewee would be able to understand the context of our study. We think that providing this information to the participants will not affect the way they answer our interview questions. Furthermore, we presented the informants an opportunity to stay anonymous in any way they felt it was necessary, in terms of concealing their real names, names of their companies, locations etc.

4 Empirical Findings

In the previous chapter we gave an overview over the research methodology that we apply in our study, with relation to the relevant methodology literature. Having explained our approach and briefly introduced the nature of the organizations that we assess as well as their representatives which were valuable informants for our study, in this chapter the main focus will be on two themes. First, we provide information in order to give a rich description of the cases we use to build our study on. Finally we present our findings from the analysis of the interviews as our empirical data.

4.1 Case Organizations

Our study is based on the analysis of the interviews we did with decision makers who are mainly in the upper level management in the organizations they are working in. The predictive analytics plays an important role for supporting their decision-making process. Four of the respondents we had an interview with accepted to reveal the identity of their companies to the public while the other two preferred to keep it anonymous. Nonetheless, in this section we present information about the six organizations we assessed in order to build our cases.

4.1.1 T-Mobile

T-Mobile Macedonia is the largest mobile operator in Macedonia and is part of the international T-Mobile family of Deutsche Telekom that provide services for more than 120 million customers worldwide. The company is active in Macedonia since 1996. T-Mobile Macedonia is considered the leader of mobile telecommunication in Macedonia. The company provide the latest services for 1.3 million of their subscribers who constitutes roughly 50% of the Macedonian market. The number of employees is over 1500 employees. The company provides services for their customer through 130 sales and customer care shops. From retail perspective, T-Mobile offers their customers a wide range of products in terms of mobile and fixed telephony packages, mobile phones, tablets, computers, TVs and IPTV and internet services. In 2013 the company has achieved profitability of 1.9 million dollars. (T-Mobile Macedonia AD, 2013).

T-Mobile has a very complex relationship with predictive analytics, using advanced systems on which they rely on when predictions should be made about their customers' behaviour, market trends and competition behavior (Appendix B).

4.1.2 DBank

DBank is one of the largest and leading banks in Macedonia. The bank is one of the pioneers in financial sector in this country. It has laid the groundwork for financial and banking operations and still is in the lead of the banking sector in both implementation and development.

The bank is part of a big banking corporation which is one of the largest banking groups in southeast Europe. DBank has over 1000 employees which provide financial and banking services for large portion of clients in the country and reaches multi-million euro in profit in the past years. The bank is supporting its growth and competitiveness through implementation of sophisticated information systems and new organisational structure. (DBank, 2013).

From retail point of view, DBank offers multiple products to customers in terms of different credit or debit cards, various savings and crediting packages. They use predictive analytics to categorize customers, to track, analyze and predict customers behaviour so they can offer the right products to the right customers. (Appendix C).

4.1.3 One (Telekom Slovenia Group)

One (Telekom Slovenia Group) is the third largest telecommunication provider in Macedonia. The company is a leader in Macedonia to offer a wide range of digital communication services ranging from mobile services, digital TV, Internet broadband, and cloud services for both in individual and business customers. It is part of the Telekom Slovenia Group which is successfully active in some south-eastern Europe countries like Albania, Kosovo, and Bosnia and Herzegovina. One has more than 0.5 million subscribers in Macedonia which constitutes about 23% of the Macedonian market. (One Telekom Slovenia Group, 2012).

One uses predictive analytics in order to build various models which predict the customers' behaviour and sales trends, based on which they make important decisions as building product packages, marketing campaigns and targeting customers (Appendix D).

4.1.4 C-Retail

C-Retail is a Macedonian company which is a major retailer, exclusive importer and premium reseller of major international brands like Apple, XXXXX, Motorola, OKI and others in the Balkans. They provide their customers with complete integration and maintenance services. Additionally, C-Retail provides various complete IT solutions and IT consulting services in the Balkan region. Their IT solutions range from ERP, CRM, Business intelligence and document management system. (C-Retail, 2011).

Similar to the other companies, C-Retail incorporates predictive analytics in their retail segment in order to make predictions of future trends about their sales and customers' behaviour. That way they constantly grow their business by offering the right products to customers. (Appendix E).

4.1.5 IKEA Sweden

IKEA Sweden is part of a multinational company that both designs and sells ready to assemble modern furniture. It operates in more than 40 countries, has 361 stores and 164000 employees worldwide. Their sales were about 30 billion Euros in 2014 worldwide. The company has a complex organization structure which depends of the country it operates in. It has a focus on cost control, operational details, and continuous product development in order to raise the operational efficiency. The company depends on several IS applications in order to achieve their goals in cost control and high sells. (IKEA, 2014).

IKEA is assisted by predictive analytics in terms of predicting sales and customers' behaviour which in fact helps them achieve higher sales of their products, minimize the time the products spend in storage and optimize supply (Appendix F).

4.1.6 Semos Group

Semos is one of the leading companies in Macedonia that provide IT consulting services, software solutions, system integration, as well as development, implementation and technical support of IT solution. They exist in Macedonia for over 20 years and have worked with numerous clients from various industries. (Semos Group, 2008).

As an IT consultancy, they offer development, implementation and technical support for systems that use predictive analytics and are able to do predictive modelling in various aspects. These solutions are mainly offered to clients that do retail. Additionally, the consultants provide training and education to business and IT users of the systems and are familiar with how their clients use the systems for predictive analytics, what it does for them and what are their perceived benefits and problems. (Appendix G).

4.2 Analysis

In this section we are going to show the results from our analysis of the generated empirical data. The perceived effects that the predictive analytics has on the decision making in organizations will be presented in terms of using the Simon's model of the decision-making process and testing the propositions of Huber's theory of the effects of advanced information technologies on organizational design, intelligence and decision making.

4.2.1 Simon's model of the decision-making process

The results in this section are structured in three groups, in accordance with the phases of the decision-making process (Simon, 1977). The categories are the following: intelligence phase, design phase and choice phase.

Intelligence Phase

The use of predictive analytics for T-Mobile implies continuous gathering of data from various sources, data which quantity is rising and that trend will only keep increasing in the future. Processing that data with predictive analytics helps T-Mobile convert it into information and into knowledge later on which leads them to have a better understanding of their surrounding environment. Our informant from T-Mobile shared the example of using customers' turn prediction where T-Mobile develops models which they use in order to predict which customers are likely to turn to other competitors and also indentify the reasons for that. They identify patterns in customers' behaviour and use those patterns to predict and make influence on the customers' behaviour in the future. They also categorize customers in different categories, identify most vulnerable group of customers which they can later address in various manners. Predictive analytics most certainly helps T-Mobile to identify potential problems, new opportunities and set decision criteria which are to be addressed in the design and choice phase of the decision-making process. (Appendix B)

Interviewees at DBank associated the use of predictive analytics with increasing trends of data collection and reproduction, saying that “analytics have this in their nature” (Appendix C, p.73). Additionally as one engages into doing predictive analysis, often the results from a certain analysis trig for making additional analyses which at the end of the day, leads to generating even more data and information that is further processed. That indicates that the use of predictive analytics increases the information collection and sharing, as actions connected with the intelligence phase. (Appendix C).

Predictive analytics plays a critical role in the retail segment of DBank’s line of work. Some of the applications of predictive analytics that the interviewees shared with us which can be related to assisting the intelligence phase according to Simon’s model are the following: “identifying sub segments of our portfolio, identifying new opportunities, identifying which customers are eligible for offering new products, which customers are eligible for offering more matured products, or which customers are maybe showing behaviour that is risky for us or other perspective behaviour that is sending signals to us that customers are using less our services and maybe using the services of some other bank” (Appendix C, p.72). It can be noted that all those examples are to be related with identification of possible problems or new opportunities as activities associated with the intelligence phase. Regarding the identification of decision criteria as a task of the intelligence phase, it appears that the criterion is defined in advance and predictive analytics does not play a role there. (Appendix C).

Predictive analytics helps One to generate information and knowledge, while they use their predictive models. They gather data about past events which they process and retrieve information out of. In addition to that, communication among departments is increased in terms of sharing various information amongst them, which would further be required in the next phases in the decision-making process. (Appendix D).

Furthermore, by predicting various events and trends, One manages to identify different patterns in customers’ behaviour which are to be addressed in the further phases of the decision-making process, so that the company can respond accordingly. Some examples of areas where patterns that are being identified, are related with: roaming patterns, behaviour in prepaid, subscriber flows, internet usage, fixed telephony usage etc. Having identified the patterns which are interpreted as problems or opportunities for the company, One is aware of the context, of the environment that surrounds them and they are able to work on setting the decision criteria for the next phases in the decision-making process. (Appendix D).

The predictive analytics stimulates C-Retail to look for new data, to analyse that data and make conclusions based on it. The amount of data that they constantly gather is on the rise, as well as the quality of the data itself. The predictive analytics depends on the collection of information and the demand for information increases. In addition to that, the information has to be shared among other employees within and cross-departments so that it can be assessed according to the needs of the company. (Appendix E).

Furthermore, the use of predictive analytics is perceived to be helping C-Retail indentify problems and new opportunities by understanding the patterns of how the customers and their competitors behave. The analyses they do help them predict demands or fill in gaps in various segments of the market which again, shows that the predictive analytics facilitates the identification of new opportunities. When they are enabled to get a better understanding of the environment they operate in, they realize what types of decisions they are required to make and the possible consequences of those decisions. That is to be related with identifying and prioritizing over decision criteria, as tasks of the intelligence phase. (Appendix E).

For the case of IKEA, we find that the predictive analytics supports the intelligence phase of the decision-making process in a very strong way. The information that they gather based on predictive analytics is constantly increasing, together with the demand for more information. Additionally they actively process it, share it between departments, and come up with various conclusions and findings to support the decision-making process. Employees at IKEA indentify various patterns in customers' and market's behavior and trends, they classify their customers and products in multiple groups, based on which they find various problems or opportunities for them to increase sales and grow their business. (Appendix F).

Similar to all the findings we had from the analyses of the other interviews, the consultant from Semos points out how big the strategic importance of the predictive analytics is, when discussed in the frame of the intelligence phase of the decision-making process. The predictive analytics stimulates the collection of information and is responsible for the constant growth of data in the organizations. Furthermore, it helps organizations to identify problems and opportunities, recognize patterns in various events and behavior and use them to grow their business. The predictive analytics supports all the activities related to the intelligence phase of the decision-making process (Simon, 1977). (Appendix G).

Design Phase

The informant from T-Mobile gave several examples in the interview we made with him, which point towards the fact how predictive analytics facilitates the design phase in the decision-making process, according to Simon's model. With the use of predictive analytics, T-Mobile models the market behaviour and makes analysis when they need to launch new products on the market by building and evaluating different scenarios. The interviewee states: "We can test and make different types of scenarios to see which one is the most valuable for us. We can make different type of assumptions what will happen on the market in the next 5 years. Then we see what would be the role of the major players on the market" (Appendix B, p. 67). They also determine the likelihood of the scenarios and make decisions that are followed with actions which will steer the business in a certain desired direction. In addition to that, T-Mobile sees predictive analytics as a unique resource for the company to explore the options when they are supposed to make various decisions. It is something that is going to develop more and more in the future to be able to optimize the business and support them in making informed decisions. (Appendix B).

Our interview at DBank reveals that the use of predictive analytics is well associated with creation and analysis of various scenarios. They have the practice of developing several scenarios among which the ones with the greatest importance are the worst and the best case scenario. What the predictive analytics does there is assist them into quantifying, evaluating and comparing the various possible outcomes of the scenarios, upon which they have to make a decision. The development of those scenarios is to be associated with the process of finding alternatives at the design phase in Simon's model (Simon, 1977). In addition to that, the analyses conducted on the scenarios are related to alternative evaluation, comparison and prioritizing. (Appendix C).

Similarly, the use of predictive analytics assists One to build various scenarios which are then analyzed, evaluated, compared and assigned with different priorities. The scenarios that they develop based on the use of predictive analytics include changing various parameters and observing the movements of revenues, traffic or number of subscribers to their services. It can be concluded that the predictive analytics plays an important role in all the tasks associated with the design phase of the decision-making process. (Appendix D).

The use of predictive analytics at C-Retail is associated with finding multiple scenarios which are then being analysed in the decision-making process. Those scenarios are considered to be a vital part in the company's line of work. Our interview with C-Retail reveals that all the actions that include identification, evaluation, comparison and prioritization of scenarios as part of the design phase, are fully supported by the use of predictive analytics. The predictive analytics is a key resource for management when it comes to the design phase of the decision-making process. (Appendix E).

Furthermore, through various examples our interviewee from IKEA illustrated how important role the predictive analytics has in the design phase of the decision-making process. They are able to generate and evaluate multiple scenarios to see the possible outcomes, for instance when they are supposed to sell different pieces of interior. Besides, their sales often highly depend on the place where the furniture is exhibited in their stores and the system takes that factor in consideration when the scenarios are being evaluated and prioritized. (Appendix F).

Our interview with the consultant from Semos reveals findings that are consistent with the results obtained from the other interviews. The consultant argues that the biggest advantage that the predictive analytics has is the ability to enable the development of scenarios about the concrete area of analysis (market analysis, customer behavior etc.). The scenarios are later analyzed, evaluated, compared and prioritized which shows the support of the design phase according to Simon (1977). (Appendix G).

Choice Phase

Predictive analytics helps T-Mobile to create and assess multiple scenarios related to a certain decision and courses of action that are supposed to be taken. However, the talk with our informant from T-Mobile indicates that predictive analytics has a big role in the intelligence and design phase, but it does not assist the choice phase in the decision-making process according to Simon's model (Simon, 1977). Even though decision makers are provided with various scenarios and means to compare their outcomes while seeing the potential likelihood of each to occur, the selection of an alternative is associated with a human factor only. The decision makers are the ones that ultimately select an alternative when making decision and the selection is not an automated process. Predictive analytics is not something that T-Mobile can only rely on, since there are external factors in decision making that systems cannot take into consideration. Also, the interviewee adds: "never underestimate the power of ideas of bringing something totally new in the business, for which there was no prior record, there is no prior trace in the data" (Appendix B, p. 65), which can be great way to grow the business. (Appendix B).

When evaluating the activity of alternative selection, regarding the choice phase of Simon's model (Simon, 1977), through the interview with DBank we found that even though the human factor has the final word when it comes to choosing an alternative in the decision making, they are assisted by predictive analytics in the choice phase. To be more clear, the predictive analytics tool or system that they are using is able to select an alternative, elaborating the case around it. Again, it is up to the human factor to make the final decision, but it is also very important to specify that the choice phase at DBank is being facilitated as well, unlike the other companies we had the chance to talk to. (Appendix C).

Regarding the way how selections of alternatives and choices are being made at One, it must be concluded that the predictive analytics does not help them in any way regarding these phase of the decision-making process. Interviewee points out to the fact that many factors need to be considered when the desired alternative is selected, in order to make sure that the course of action will be in line with company's business goals. The predictive analytics assists them in the previous phases of the decision-making process, while it is up to decision makers themselves to do the alternative selection. (Appendix D).

The selection of the best alternative when making a decision cannot be related to the use of predictive analytics at C-Retail as well (Appendix E). Interviewee points out to potential flaws and imperfections of predictive tools and models as they are not able to incorporate various external factors that influence the selection of the right alternative for the company (Appendix E). The choice phase continues to be solely dependent on human factor, or on the decision makers, to be more precise (Appendix E). The case is rather similar at IKEA where the predictive analytics is not perceived to assist the choice phase of the decision-making process (Appendix F). What the interviewee from IKEA pointed out is that the predictive analytics has critical role in providing information, predicting the likelihood of various scenarios to happen while the final choice of action is always left to the decision makers and their experience (Appendix F).

The consultant from Semos perceives that it is up to the human factor, or decision makers to make the final call, to make the selection of the scenario they want to go with. Comparable to findings we had from the other interviews, the consultant mentions other external factors that decision makers often incorporate when making a decision (politics, economics, legislation) which cannot be predicted but yet influence the section of a course of action. Therefore, the consultant perceives that predictive analytics does not influence the choice phase of the decision-making process, according to Simon (1977). (Appendix G).

4.2.2 Huber's theory of the effects of advanced information technologies on organizational design, intelligence and decision making

The results in this section are presented in four groups, in accordance with the categories of variables and propositions in Huber's theory (Huber, 1990). The categories are the following: effects of the use of predictive analytics at subunit level, effects of the use of predictive analytics at organizational level, effects on organizational memory and effects on organizational intelligence and decision making. Within each category, there is a subcategory which is related to the corresponding assessed variable.

Effects of the use of predictive analytics at subunit level

Participation in decision making

Thinking about the number and variety of people that generate knowledge associated with the use of predictive analytics which is later used for making decisions, our interviewee from T-Mobile points out to possible differences between different industries that would be related to different characteristics of the data they are dealing with. One thing he says is that more people with different backgrounds are needed to collect and process the required data, while the developed IT capabilities help reducing the number of people that should analyze all that data. Still, he concludes with: "I know for sure, we had much less people 10 years ago, working on data analytics than we have today" (Appendix B, p. 68) indicating the increased number and variety of people that participate as information sources in the process of decision making. (Appendix B).

Similar to what the informant from T-Mobile stated, DBank has way more open positions in multiple departments that are dedicated to analyzing data and making predictions generate information so that decisions can be made (Appendix C). That clearly shows that the use of predictive analytics at DBank leads to increased number and variety of people participating as information sources. (Appendix C). When it comes to contributing in the decision-making process in terms of providing information and knowledge, with the use of predictive analytics more people are required to participate at One (Appendix D). Additionally, in order decisions to be made, people from different departments are required to make predictions about occurrences of various events, based on historical data (Appendix D). That indicates that larger number and variety of people participate as information sources with the use of predictive analytics (Appendix D).

The interviewee at C-Retail describes how the use of predictive analytics stimulates the creation of knowledge in the decision-making process. Through examples he indicates that predictive analytics demands people from different departments to work with the data and make predictions which are later used in decision-making processes. Those predictions which are results from the use of predictive analytics, represent information that is base for making decisions, while the people delivering it are its sources. Having a scenario as a reference point where predictive analytics is not used, the use of predictive analytics leads to a larger number and variety of people contributing as information sources to decision making. (Appendix E).

The case with IKEA is similar and an example of that is that the sales clerks are using predictive analytics and frequently provide information or raise potential issues to the sales managers. The sales managers on the other hand, are able to make an informed decision based on the information they got. In fact, the predictive analytics increases the number and variety of people that contribute to the decision-making process as being information sources. (Appendix F).

The interview we had with the consultant from Semos confirms the findings we obtained from the interviews with the other companies. The consultant has the same perception as the others interviewees regarding the participation in decision making as information sources. With predictive analytics more people are enabled and required to analyze data and provide valuable input in the decision-making process. (Appendix G).

Size and heterogeneity of decision units

At T-Mobile decisions are kept standardized, lower level management and employees make decisions about everything that they can and that is supported by predictive analytics. Later on, KPIs are being sent to upper management which they use to make certain decisions. Nonetheless, decision units are comprised of fewer members and less diverse, by empowering individuals to make all the decisions that they can. (Appendix B).

On the other hand, the results from our analysis are rather different at DBank and One. Our interviewee from DBank refers to the needed safety and precaution when making decisions in the banking industry as a main reason why they require larger variety and number of people to be part of the decision-making process (Appendix C). Taking into consideration that predictive analytics is an advance information technology which is used by various departments to predict various aspects of the business working of the company (market analysis, customers' behaviour, different trends etc.), the decisions that it supports are rather complex for One (Appendix D). Accordingly, when decisions are perceived as complex, the number and variety of people that comprise the decision units is increased. (Appendix D).

Our interview reveals that predictive analytics assists C-Retail to predict outcomes for events of different types, outcomes which are to be presented to decision makers. Regarding the size and heterogeneity of the decision making units, less number and variety of people is required to do a further analysis to be able to make the decisions, because the needed information is already present to the decision makers. (Appendix E). The interviewee from IKEA argues that the predictive analytics helps them make the decisions easier and faster and they have no need to consult many people when something needs to be decided (Appendix F). The predictive analytics and the standardization of procedures when it comes to deciding have helped them to decrease the number and variety of people that comprise the decision units (Appendix F).

The opinion that the consultant has regarding the influence on the size and heterogeneity of decision units is that predictive analytics stimulates reduction of the number and variety of people that comprise the decision making units. With the right set-up of the predictive analytics system the organizations need less people and less diverse people to make decisions, which is in line with Huber's theory (Huber, 1990). (Appendix G).

Frequency and duration on meetings

The interviewee at T-Mobile argues that the use of predictive analytics provides "better view to the top management and better answer for all questions that you need to have in mind"(Appendix B, p.68), so that they come up with more informed decisions. Familiar with the benefits of it, their hunger for information does not stop and they demand for more meetings. Even though the effectiveness of the meetings is increased, therefore their duration is reduced, the frequency of the meetings related to decision making is much increased. That results in more of the organizational time consumed by decision making meetings. (Appendix B).

We reached the same finding when analyzing the interview with our informants from DBank. They perceive that the use of predictive analytics requires more organizational time spent on meetings about reaching a certain decision. The reason for that perception is that results of the analytics not always are interpreted and presented in the right way, so decision makers require more time on meetings. (Appendix C).

The use of predictive analytics helps One to obtain valuable data in a timely manner which is well communicated with the participants of the meetings (Appendix D). That way the need for meetings is not as frequent as it would be without predictive analytics and meetings tend to last less time for them (Appendix D). Additionally, in the future they believe that meetings would last even less time when the predictive analytics evolves more (Appendix D). Predictive analytics enables C-Retail to process data, extract information and make predictions about future events (Appendix E). That information is considered to be valuable by the management, they rely on it when it comes to having meetings about making decisions (Appendix E). That way the decisions are reached in a faster way. Furthermore, meetings are perceived to last shorter and with reduced frequency, due to the use of predictive analytics (Appendix E).

Our interviewee from IKEA reveals that the use of predictive analytics is not perceived to be affecting the time and frequency of meetings regarding decision making in terms of increasing or decreasing them. To be more precise, the predictive analytics is perceived to affect only the topics of discussion and how the discussion would proceed. Before using predictive analytics, they spend more time discussing the data and the possible scenarios, while now when that is taken care of by the predictive analytics, they spend more time on planning. Nonetheless, the same amount of time is perceived as consumed in meetings at IKEA. (Appendix F)

Regarding the time consumed on meetings regarding decision making, the consultant from Semos generally perceives that the use of predictive analytics has no direct influence it. The reason behind that is that meetings always rely on data and information which must be there as an "independent variable" in order for the meetings to take place. The predictive analytics significantly reduces the time needed to obtain that information and therefore speeds up the decision making, while is not perceived to affect the time consumed on meetings by the consultant. (Appendix G).

Summary of the results we obtained analyzing the perceived effects of predictive analytics at subunit level and testing the propositions in this category can be found in Table 4.1.

Table 4.1 Empirical results about the effects at subunit level

Company	Proposition 1	Proposition 2	Proposition 3
T-Mobile	✓	✓	×
DBank	✓	×	×
One	✓	×	✓
C-Retail	✓	✓	✓
IKEA	✓	✓	-
Semos	✓	✓	-

Effects of the use of predictive analytics at organizational level

Centralization of decision making

Regarding the variable of centralization of decision making, the interviewee from T-Mobile reveals that people from different hierarchical levels are enabled to make certain decisions with the use of predictive analytics in the company. At lower hierarchical levels, some of those decisions are standard operational practice and their outcomes are on a good, satisfactory level for the company while the various risks related to them are eliminated. The ability of different hierarchical levels to make decisions for the company that are supported with the use of predictive analytics indicates a decentralizations in the decision making, in a highly centralized organization as T-Mobile. (Appendix B).

In addition to that, we obtained similar findings from our interview with DBank, where employees who are even in lower hierarchical levels and working in a single branch of the bank as bank officers, are empowered by predictive analytics to decide about making certain offers to customers that enter in a bank's branch looking for particular services (Appendix C). Predictive analytics definitely helps DBank to decentralize decision making as much as possible, considering that they are a highly centralized organization (Appendix C). Predictive analytics especially empowers the people of the middle level management at One, to make decisions related to various aspects of the company (sales, processes, issues etc.) (Appendix D). While the top level management has a hold of the big image for the company, their strategic moves are based on the decisions that come from the middle level management who have insights with greater detail and depth in the domain they manage (Appendix D). That shows that the use of predictive analytics allows more decisions to be made at the lower hierarchical levels, which leads to decentralization of the decision making in a highly centralized organization as One (Appendix D).

Employees at all hierarchical levels at C-Retail are empowered to make all the possible decisions they can, without the need to get a special approval from their superiors. Naturally, they are empowered to make certain types of decisions that are in line with their hierarchical level of the company and decisions about which they have the needed information and knowledge. Predictive analytics in fact assists them in the part where the needed information and knowledge is being generated. So when predictive analytics is being used, people in the middle and lower management of the company are able to obtain the needed knowledge and make decisions without the need to check with the top management. That indicates that the use of predictive analytics supports the decision making in C-Retail in a way which leads to increased decentralization in a centralized organization like they are. (Appendix E).

In the case of IKEA, the use of predictive analytics enables personnel from the lower hierarchical levels in the company to make decisions with a good level of quality. The interviewee shared an example where sales leaders in stores are able to come up with decisions in their line of work, without having the need to consult with higher level management before acting. That indicates the decentralization of the decision-making process in IKEA which is supported by the use of predictive analytics. (Appendix F).

Our interview at Semos revealed findings that are consistent with the perception of all the other companies. The consultant argues that with the proper hierarchical organization and the right system that incorporates predictive analytics, employees at lower hierarchical levels in companies are provided with means to make certain decisions corresponding with their level. That way the organizational processes are more optimized and the decision-making process is being decentralized. (Appendix G).

Number of organizational levels involved in authorization

Authorizing a certain action is considered to be identical with making a decision T-Mobile and with the use of predictive analytics employees in the lower hierarchical levels are enabled to make decisions, which also means those people authorize actions as well (Appendix B). The number of organizational levels involved with authorizing actions is thereby reduced with the aid of predictive analytics (Appendix B). The exactly same findings are to be present about the case at DBank. The decentralization of decision making supported by predictive analytics leads to reducing the number of organizational levels that should participate in the making of certain decision (Appendix C). That also means that the number of organizational levels involved in authorizing action about a certain decision is also reduced with the use of predictive analytics (Appendix C).

The decision-making process is shortened with the use of predictive analytics at One, employees at lower managerial levels are empowered to make decisions thus decentralizing the decision-making process. Authorization for actions is considered as a formality which automatically follows the decision-making process. Since the number of hierarchical levels involved in decision making is practically reduced, we can conclude that the same goes for the number of hierarchical levels involved in authorizing actions. (Appendix D).

Since the decentralization at C-Retail is increased in terms of decision making and the authorization of actions is identified as being almost the same process as decision making, it is safe to conclude that the number of levels that need to authorize the decisions are also reduced (Appendix E). Predictive analytics helps the lower hierarchical levels in the company to make informed decisions thus leading to increased decentralization in the decision making, and that also means those people authorize the actions accordingly (Appendix E). Similarly, at IKEA the use of predictive analytics provides sales leaders with means to make certain decisions and act based on them (Appendix F). Those actions do not require any authorization from the upper hierarchical levels, therefore the number of levels involved in the authorization of action is reduced with the use of predictive analytics (Appendix F).

Similar to the other companies, the consultant from Semos states that when using predictive analytics employees at lower hierarchical levels can make the right decisions for their organization. Additionally, most of the times there are strict rules so employees can authorize actions without seeking approval from their superiors, therefore predictive analytics helps reducing the number of nodes included in authorization of actions within the organizations. (Appendix G).

Number of nodes in the information-processing network

With the growth of the demand for information in all in the organizational departments, the need for communication is constantly increasing at T-Mobile. The evolution of IT and the use of predictive analytics helps people directly obtain certain information that they need in order to make a certain decision or produce various reports and calculations. That way less people are required to process various data and information in order to present it to others so that actions could be made. That shows that the use of predictive analytics leads to fewer intermediate human nodes needed, in the organizational information-processing network. (Appendix B).

Employees at DBank are required to communicate more and exchange more data with other employees within and crossing departments (Appendix C). The predictive analytics is perceived to be increasing the number of intermediate nodes in the organization's information-processing network, so that a certain decision can be made (Appendix C). Similarly, the various events that One needs to predict as a company are perceived as complex and in order to make those predictions, a lot of information needs to be exchanged between employees (Appendix D). The parameters that determine the outcome from the predictions are interconnected, thus information often needs to be processed and exchanged across departments (Appendix D). That indicates that the use of predictive analytics demands more intermediate nodes in the organizational information-processing network.

Since multiple departments in C-Retail use predictive analytics for various purposes and their line of work is dependent on information that comes from the other departments, people are required to communicate more. While they communicate more, they are also supposed to process the information obtained from the other departments so that they are able to make informed decisions. That points out that even though predictive analytics supports the departments to have knowledge to make decisions, they are more dependent on each other's work and the number of intermediate nodes within the organizational information-processing network is not reduced. (Appendix E).

From the analysis that we did on the interview with IKEA, our findings are that the use of predictive analytics reduces the number of nodes that are involved in the information-processing network within the organization. The systems that IKEA is using enable their users to obtain the right information, the right predictions in the right moment when they are needed so that decisions can be made. That means that the information does not need to travel and to be processed between multiple nodes until it reaches its final destination. (Appendix F).

The consultant perceives the use of predictive analytics to be reducing the number of nodes in the information-processing network within organizations. An indicator for that is that there are less people needed to process certain information and provide input for the complex processes of analyzing data. That way decisions are being made in a faster and simpler way. (Appendix G).

A summary of the results we obtained when testing Huber's propositions about the effects of predictive analytics at organizational level (Huber, 1990) can be found in Table 4.2.

Table 4.2 Empirical results about the effects at organizational level

Company	Proposition 4	Proposition 6	Proposition 7
T-Mobile	✓	✓	✓
DBank	✓	✓	✗
One	✓	✓	✗
C-Retail	✓	✓	✗
IKEA	✓	✓	✓
Semos	✓	✓	✓

Effects on organizational memory

Development and use of data bases

Following a global trend among the organizations worldwide, the amount of data which is generated and processed by T-Mobile is huge, compared to what it was like for them ten or twenty years ago. The interviewee is sure that this trend is not going to stop and in the future they will be gathering and analyzing data about everything their customers do, so that they can predict their behaviour. The use of predictive analytics demands for more frequent development of databases and other organizational memory components so that all the gathered and collected data as result from various analyses can be stored, which is in line with proposition 8 from Huber's theory (Huber, 1990). (Appendix B).

Our findings are similar for the case of DBank where the interviewees state that the results they get using predictive analytics, often trig more and more analyses which generate even more data (Appendix C). The data must be stored, accessed and processed so the development and use of data bases at DBank is definitely more frequent with the use of predictive analytics (Appendix C). The use of predictive analytics and the experimentation with various models to be able to draw conclusions at One depends on the amount and the quality of the data that they have (Appendix D). The amount of data is rising continuously and the results from the analyses that they conduct are also data which need to be stored somewhere and managed (Appendix D). The predictive analytics simply demands constant work on the data management part, constant development of data bases and management of the data in the warehouses, in order to ensure stable working environment (Appendix D).

The interview with C-Retail shows that the amount of data that they are gathering, analysing and also producing as a result of their analysis is constantly growing. The growing trend is not perceived as it would stop at any time soon, but instead it would continue growing since data is the key resource for conducting predictive analytics. When so much data is being gathered, naturally comes for C-Retail to have an increased need to store that data. The more frequent development and use of databases is a logical consequence of the use of predictive analytics (Appendix E).

The case of IKEA appears to be the same, according to the interview that we did with them (Appendix F). With the use of predictive analytics they generate and process a lot of data and its quantity is (Appendix F). That indicates that they must continuously use and develop components of the organizational memory, to be able to address the need that rises with the use of predictive analytics (Appendix F). Similar to what the other interviewees stated before, the consultant from Semos argues that the predictive analytics generates more and more data (Appendix G). Organizations must constantly explore ways how to store and manage it in the right way and naturally, they are required more frequently to develop data bases as components of organizational memory (Appendix G).

Development and use of in-house expert systems

Our interviewee from T-Mobile makes a connection of the use of predictive analytics with the needs for developing data warehouses and changing (updating) the ways they are created and accessed. He sees the updating of those procedures as an unavoidable necessity, a triggered response from the development and growth of IT, especially referring to predictive analytics. The use of predictive analytics demands for updating the procedures which in fact leads to more frequent development and ussage of data warehouses as parts of expert systems, components organizational memories. That is in line with the proposition 9 from Huber's theory. (Appendix B).

In the case of DBank, we find that the predictive analytics has an influence over the procedures for development of components of the organizational memory which leads to more frequent development and use of the components (Appendix C). In fact, the predictive analytics stimulates the growth of data which stimulates the increase of the need for development and use of organizational memory components (Appendix C). As a response to that, DBank has to make the procedures more user-friendly, which is in line with Huber's theory (Huber, 1990). Regarding the procedures for development of in-house data warehouses, expert systems as components of organizational memory at One, the use of predictive analytics is linked to the needs for updating those procedures (Appendix D). As the new and updated procedures are being made more flexible and user friendly, the growth of the data is supported in a better way and the use of predictive analytics is better facilitated (Appendix D).

Our interview at C-Retail reveals that the need for development of knowledge repositories as components of the organizational memory is increased because of the use of predictive analytics. However, the procedures for constructing knowledge repositories which would lead to development of organizational memories according to Huber (1990) are not perceived to be affected by the use of predictive analytics. (Appendix E).

In the interview with the informant from IKEA we were unable to obtain information about how predictive analytics influences the procedures for development and use of organizational memories and assess the influence accordingly. The reason for that lies in the organization and structure of the company, where the sales managers are more focused on their key activities. The information that we seek can only be obtained from the IT department which is not our target interview group. (Appendix F).

The analysis we did of the interview with Semos shows similar results as the findings in most of the companies we interviewed. The volume of data that the predictive analytics participates in generating directly affects the procedures the organizations have for development and use of organizational memories. Procedures are often updated in order to provide more flawless operation of the predictive analytics. (Appendix G).

In Table 4.3 we present a summary of the results we obtained when testing Huber's propositions about the effects of predictive analytics on organizational memory (Huber, 1990).

Table 4.3 Empirical results about the effects on organizational memory

Company	Proposition 8	Proposition 9
T-Mobile	✓	✓
DBank	✓	✓
One	✓	✓
C-Retail	✓	×
IKEA	✓	n/a
Semos	✓	✓

Effects on organizational intelligence and decision making

Effectiveness of environmental scanning

Assessing the variable of effectiveness of environmental scanning, our interview with T-Mobile shows that the use of predictive analytics most certainly helps their organization in many aspects, for example to identify likelihood and reasons for customers turning to their competitors, model customers behaviour, identify vulnerable categories of customers, find new opportunities and even develop future forecasts and plans on which their business plans depend on. Additionally, with those predictions being made, problems and opportunities are being discovered quickly while being perceived as valid and correct. That indicates that the use of predictive analytics helps T-Mobile identify problems and new opportunities in an accurate and timely manner. (Appendix B).

In addition to that, the interview we conducted with DBank shows that the predictive analytics assists the bank to rapidly and accurately obtain new opportunities and possible problems. Through multiple examples that they introduced during the interview, it can be noticed that the predictive analytics is valuable resource for them which provides them with means to understand their customers' behaviour. That way they are able to offer the right products to the right customers at the right time. (Appendix C).

One learns how customers (subscribers) behave in given circumstances and predicts their behaviour in a fast way. Even in situations where the company lacks information on some parameters, they are able to create models through which they can inspect how customers' actions are going to affect their business in near future and make decisions having that input. The fact that the information from the models is included in the budget planning both for the near future and the next five years which shows that predictive analytics is being perceived by the company as an accurate mean of identification of problems and opportunities. (Appendix D).

Furthermore, C-Retail does not base their decisions on a "gut feeling", but instead they heavily rely on data. Data is constantly gathered and used for analysis where predictions about future events are made. The interview shows that predictive analytics helps C-Retail identify problems and new opportunities in a quick manner, and even support important strategic decisions like the case with entering new markets – which proves the perceived accuracy of the identified new opportunities through the use of predictive analytics. (Appendix E).

Similar to the responses that we got from the other informants, the interviewee from IKEA points out to the increased effectiveness of scanning the environment when predictive analytics is being used. The interviewee connects the predictive analytics with identifying and understanding patterns of consumers' behavior and market and sales trends which can be easily and quickly obtained. The results from the analyses are perceived as accurate which is why they base important decisions on them. (Appendix F).

Consistent with all the findings we had from the analyses of the interviews with the other companies, the consultant from Semos argues that the organizations that use predictive analytics certainly are able to identify new opportunities. Those organizations are able to make more advanced scanning of the environment that surrounds them, mainly in terms of getting better understanding of the market and the customers they work with in a fast and accurate way. (Appendix G).

Quality and timeliness of organizational intelligence

The interviewee from T-Mobile mentions an example about customer turn prediction (determining customers that are likely to turn to T-Mobile's competitors), the modelling that they do and how much it helps them to prevent their customers to leave (Appendix B). Through that, we can see that predictive analytics increases the knowledge that the organization has and its perceived quality, accuracy, timeliness are improved when compared to a case where predictive analytics is not used (Appendix B). In addition to that, the use of predictive analytics is perceived to be increasing the availability and quality of the organizational knowledge for DBank (Appendix C). Throughout multiple examples given in the interview, the interviewees argue how valuable resource the predictive analytics is, for the organizational intelligence (Appendix C). Everything they learn through the use of predictive analytics about the behaviour of their customers in a timely way is later being used to help the bank respond to the needs of their customers (Appendix C).

The rapid and accurate problem identification at One which is achieved through predictive analytics, combined with analysis leads them to creating an organizational intelligence with a high level of perceived quality, comprehensiveness and timeliness (Appendix F). Besides, the fact that the intelligence is being relied on for decisions of crucial importance for the company like budget planning confirms that finding (Appendix D). The predictive analytics demands data and the quantity of the data C-Retail has is increasing over the time (Appendix E). They must analyze that data, make predictions and generate knowledge in order to make informed decisions (Appendix E). Naturally, as the availability and the amount of data increases in fast pace, analysis must be quickly done and the knowledge for the company also increases in a fast and timely way (Appendix E).

In addition to that, the quality of the generated knowledge is perceived to be high, as it is used as a base for important decisions. Similar to that, our interview at IKEA reveals that the use of predictive analytics is perceived to help the company increase the organizational intelligence. The knowledge that they get using predictive analytics is perceived to be generated in a fast manner and with high quality and accuracy considering the fact that they base important decisions on it in terms of future sales. (Appendix F).

The consultant from Semos supports the arguments that other organizations had in our interviews. He argues that when the right tools with the right configurations are being used for the right purposes in the organizations, the intelligence that the organization gets from using predictive analytics can be generated faster and has higher quality. (Appendix G).

Quality of decisions

Regarding the quality of the decisions that are being made with the help of predictive analytics, the interviewee from T-Mobile argues that predictive analytics "is a strong tool to support the business, strong tool that contributes to making decisions, but it cannot steer the business totally" (Appendix B, p. 65). Predictive analytics is always there to help the company optimize the way that business is done but one cannot rely on it solely. Still, the use of predictive analytics most definitely leads to making decisions with higher quality. (Appendix B).

Similarly, the quality of the decisions that DBank makes using the predictive analytics is most certainly increased (Appendix C). DBank is able to construct different scenarios, monitor the possible outcomes and select the best course of action, which ultimately leads them to achieve their business objectives (Appendix C). When thinking of the quality of the decisions, the interviewee at One justifies the decisions that are being made based on the use of predictive analytics, since they prove to be accurate and have positive outcomes for the company in terms of growing their business (Appendix D). Therefore the use of predictive analytics leads to more informed decisions with higher quality. Furthermore, related to the quality of the decisions that C-Retail is making based on predictive analytics, our interview with them shows that the perceived quality of the decisions they make is very high (Appendix E). As a point of reference they use the fact that they are one of the most successful retail companies in Macedonia and the Balkans, which proves that their decision made with help of predictive analytics have a perceived high quality (Appendix E).

The quality of the decisions made which are based on predictive analytics is considered to be high at IKEA as well. An indicator of that are basically the sales that they manage to make. The predictive analytics is there to predict the future trends, the various movements of the sales based on historical data. IKEA base their decisions on that and succeed to make the right offers and achieve more sales. (Appendix F).

Closely related to the quality of the organizational intelligence obtained with the use of predictive analytics, the consultant is sure that the decisions based on predictive analytics have increased quality. In fact, he estimates that those decisions are about 70% better in terms of quality, compared to a case when predictive analytics is not used. Furthermore, he points to the importance of having high quality data that should be processed with predictive analytics, in order to have high quality decisions. (Appendix G).

Speed of decision making

When evaluating the time required to make a decision which is based on an input that comes from the use of predictive analytics, the interviewee from T-Mobile brings up the time needed to collect and process the data needed saying: “if you collect more data and you take more information into account when you make decision, it obviously means that you will spend more time” (Appendix B, p. 66). He further states that it is always a trade-off, decisions can have either a high quality related to the use of predictive analytics, or make a quick decision which comes with great risk. In addition to that, the time required for an authorization to be made of a certain action, our interviewee from T-Mobile connects that to the time needed for a decision to be made, since he relates making decisions and making authorization of an action as a one single process. Therefore, with regards to the case of T-Mobile, to sum up, the use of predicative analytics does not reduce the time needed for a decision to be made and the time required for an authorization to be made, on the account that it greatly affects and improves the quality of the decisions that they make. (Appendix B).

Discussing the time DBank takes to make decisions when using predictive analytics, our interview shows that the bank perceives that time to be reduced. That means, with the use of predictive analytics they are able to analyze scenarios and come up with a decision faster. Additionally, the process of authorizing actions is considered to follow naturally after the decision making, so if the time to come up with a decision is reduced due to the use of predictive analytics, we can conclude that the same goes for authorization as well. (Appendix C).

The use of predictive analytics and modelling is perceived to be reducing the time period required for decisions to be made at One, like for instance decisions related to budgeting and business planning. The company relies on the accuracy of models based on historical experiences and the results that they produce, therefore the management makes decisions faster. Similarly to decision making, the process of authorization of actions is reduced in time since it is considered more of a formality which follows after decision making. So, once the decision-making process is more efficient and requires less time, the same goes for the process of authorization of actions. (Appendix D).

Thinking about the time needed for a decision to be made and related actions to be authorized at C-Retail, it should be said first that authorizing an action and making a decision is referred to almost as a same process. The interviewee from C-Retail claims that they always go together. As of the time needed for a certain decision to be made, the use of predictive analytics is considered to have an effect of reducing the time required. When the tools and models are being used, data is analyzed in a faster ways, predictions are made and results can timely reach management. After that they are able to make an informed decision in a timely manner. Another insight that we got at the interview is that, it happens sometimes for the company, a certain chain of events to repeat itself, historically. Since they have done the analysis before, they are able to reuse the knowledge they have and reduce the time needed for a decision to be made. Accordingly, the same can be stated for the time needed for authorization of actions. The use of predictive analytics helps C-Retail reduce that time as well. (Appendix E).

The general perception of the time required for decisions to be made at IKEA is that the predictive analytics significantly reduces the time needed for decisions to be made on long term. That is related to more strategic decisions in a way that would influence the sales that would be done in the following year. However, we must point out that sometimes the predictive analytics slows down the making of operational decisions, brought on a daily basis, because the system demands time for inputting data. Still, that set back is compensated with the time savings in making decisions and authorization of actions for longer terms. (Appendix F).

Like most of the companies we had an interview with, the consultant from Semos perceives the predictive analytics to be reducing the time required for decisions to be made and authorizations for actions accordingly. In fact, he perceives the reduction in time to be extremely big, making it one of the biggest advantages of predictive analytics. Furthermore, he emphasizes the importance of having a sophisticated, well designed system that corresponds to the companies' needs in order to achieve the best benefits and reduce the time for decision making as much as possible. (Appendix G).

The results from testing the Huber's propositions (Huber, 1990) in order to examine the effects of predictive analytics on organizational intelligence and decision making are summarized in Table 4.4.

Table 4.4 Empirical results about the effects on organizational intelligence and decision making

Company	Proposition 10	Proposition 11	Proposition 12	Proposition 13	Proposition 14
T-Mobile	✓	✓	✓	×	×
DBank	✓	✓	✓	✓	✓
One	✓	✓	✓	✓	✓
C-Retail	✓	✓	✓	✓	✓
IKEA	✓	✓	✓	✓	✓
Semos	✓	✓	✓	✓	✓

5 Discussion

In this chapter we discuss our empirical findings elaborated in the previous chapter in the context of providing answers to our research question. We also discuss the meanings of our findings while pointing out the potential differences with the outlined theories in Chapter 2.

Starting with our research question: *What are the perceived effects of the use of predictive analytics on decision making in organizations?*, our answers will be presented through the prisms of the Simon's model of the decision-making process (Simon, 1977) and Huber's theory of the effects of the use of advance information technologies on organizational intelligence and decision making (Huber, 1990).

Predictive analytics through Simon's model

Simon explains the decision making in organizations as a complex process that consists of three phases: intelligence, design and choice phase which are the steps that must be accomplished in order for a decision to be made. Looking for answers to our research question, we used the model to break down the decision-making process into the three phases, assessing how the use of predictive analytics affects each activity of each phase in the decision making.

After analysing the empirical data that we gathered, when evaluating from a perspective on a high level, we find that use of predictive analytics is perceived to affect the intelligence and the design phase of the decision-making process. The choice phase on the other hand, mainly appears to remain unaffected with the use of predictive analytics. So the next logical question that would come in mind would be to ask ourselves, what does that mean for the decision-making processes in the organizations? That is exactly what we discuss in this section.

Intelligence phase

The use of predictive analytics helps organizations to identify problems and opportunities on which they can act and ensure that their business grows. That way, the predictive analytics represents a unique resource for the organizations since they have no other way to obtain the information they do with predictive analytics. In the end, as Davenport (2006) argues, it is up to the organizations themselves to analyze their data, predict what would happen next in order to be a winner in the competition of analytics.

In addition to that, once problems and opportunities are being identified, the predictive analytics also assists organizations in identifying and prioritizing decision criteria. The new opportunities that arise for the organization sometimes require a better understanding of the context, while the predictive analytics helps them make analysis to see what they are dealing with. That way it provides them with means to develop and elaborate criteria based on which decisions can be made. Only one organization stood out in our findings in this context, DBank and the main reason for that is the sensitivity of the industry they operate in. Decisions at banks are perceived as very sensitive and the decision criteria are mainly defined in advance, which is why our informants from DBank did not perceive the predictive analytics to help them develop decision criteria.

Furthermore, the predictive analytics stimulates the constant growth of data and collection of information at the organizations. Since they are accustomed to the benefits they have with the use of predictive analytics, they demand for more and more data while foreseeing that the trend will never end, but will continue increasing as literature suggests (Chen et al., 2012; Davenport, 2006). As the development of the predictive analytics evolves, organizations feel that in the future they will be able to know almost everything about their customers and will have new means to tackle their needs. To be able to process all the data they are having and to be able to draw conclusions of various types, people within the organization are constantly supposed to communicate and share information. By aligning the work that multiple departments do, the results from analyses done with predictive analytics and connecting them, organizations are able to grow their businesses.

Design phase

When assessing the activities related to the design phase of the Simon's model of the decision-making process (Simon, 1977), our empirical findings were consistent for all the companies we had the opportunity to do an interview with. The case is strongly supported that the use of predictive analytics helps the organizations to find and develop alternatives – possible action courses regarding the making of a certain decision. Organizations are also supported by predictive analytics to make an evaluation, compare and prioritize the developed alternatives. Furthermore, the predictive analytics is a unique resource for the organizations that are able to facilitate those actions for the specific decisions needed to be made. Therefore, the predictive analytics plays a critical role in the organizations by supporting the design phase in the decision-making process.

Choice

Regarding the question of what effects does the predictive analytics have on the activity of selecting an alternative, as part of the choice phase of the decision-making process in organizations, our findings show that the predictive analytics does not have any effects on it in the organizations. The selection of an alternative when making a decision is something that a human is entitled to do.

The possible interpretation of that is related to the sensitive and strategic character of the decisions that the predictive analytics is being used to support in the organizations. That is understandable because the management of an organization and the decisions they make cannot be simply replaced with a system that makes the decisions for them, regardless how precise the system is. Even though, one of our respondents stated that the predictive analytics is able to make choices of certain decisions for them, they emphasized that it is not fully automated process and still depends on the human factor. Therefore, the inability of the predictive analytics to support the choice phase in the decision-making process cannot be related to the level of sophistication of a certain system or tool that the organization uses. Further argument in this debate that was revealed in the interview analyses is that the management of the organizations often considers multiple parameters external to the organization, like political and economic climate, legislation, information about the competition – which are all something that no system or tool can take into consideration when making predictions of events. That again justifies the inability of predictive analytics to support the choice phase in a better way. Finally, the informant from T-Mobile shared how important is the value of new ideas being brought to the table during decision making. That refers to new scenarios, new untested and unevaluated alternatives which carry a certain degree of risk for the organizations, but still can be considered as possible alternatives to be chosen from when a decision has to be made.

Predictive analytics through Huber's theory

Huber's theory helped us analyze the perceived effects from the use of predictive analytics as an advanced information technology on organizational intelligence and decision making. In the previous chapter we analysed in detail the empirical findings of the perceived effects from the use of predictive analytics on decision making, through the frame of Huber's theory (Huber, 1990). We did that by testing the propositions that the theory is built upon and checking whether there is alignment between them and the results from our empirical data, set up in the context of predictive analytics. In this section we will interpret our findings, discuss their meanings for the organizations and explain the possible reasons for the found misalignments with theory.

Effects from the use of predictive analytics at subunit level

The effects from the use of predictive analytics at subunit level in organizations regarding the decision-making processes, are expressed with the variables: participation in decision making, size and heterogeneity of decision units and frequency and duration on meetings. The use of predictive analytics demands more people, people from different backgrounds and people from multiple departments within the companies to be able to make predictions of certain events happening in the future. As the complex nature of the events is increasing, the demand for more people increases as well. The increase of demand for more people and people with different backgrounds to work with data and make predictions indicates the increased number and variety of people that participate as information sources in the decision-making processes, stimulated by the use of predictive analytics. Those findings are consistent among all the companies we interviewed and are in line with proposition no. 1 from Huber's theory (Huber, 1990).

When examining the variable of size and heterogeneity of the decision making units in the organizations, the results that we obtained had inconsistencies among the organizations. The majority of the companies (four out of six) perceive the use of predictive analytics to be reducing the number and variety of people that are needed in order for a decision to be made, which is in line with proposition no. 2 from Huber's theory (Huber, 1990). However, DBank stands out in this case and that can be justified with the very high perceived sensitivity of the decisions that they are making, which is related to the banking industry in general. Additionally, One perceives the decisions that they are making to be complex and require increased number and variety of members comprising the decision units. The possible reasons for that could be related to the system that they are using or in the ways they do their business processes. We interpret that as a call for further analysis and optimization of their business processes.

The last variable in this category assesses the frequency and duration of meetings in relation with the use of predictive analytics, and in this case our results from the analysis appear to be most divided. To be more specific, the distribution of the answers from our informants is uniform in terms of their opinions whether the use of predictive analytics results with more time being consumed at meetings, less time being consumed at meetings or having no affection at all to the organizational time consumed in meetings. With these results we are not able to generalize our findings and make a statement whether we find the use of predictive analytics reduces the duration and frequency of meetings like theory suggests (Huber, 1990), or not. Having said that, we want to put forward the need for further research in the area.

Effects from the use of predictive analytics at organizational level

The variables that address the effects from the use of predictive analytics at organizational level are: centralization of decision making, number of organizational levels involved in authorization and number of nodes in the information-processing network. When assessing the variable of centralization of decision making in organizations that have a highly centralized structure, our results were consistent for all the companies. The predictive analytics is most definitely perceived to be supporting decentralization of the decision making in organizations, which is in line with proposition no. 4 of Huber's theory (Huber, 1990). The informants discussed multiple cases where the ability of middle management, lower management and sometimes operatives to make certain decision within their scope with the support of predictive analytics, which is the main indicator of imposed decentralization in decision making.

The decentralization of decision making in organizations that is trigged by the use of predictive analytics results with reducing the number of organizational levels involved when making a certain type of decisions. Since all of the organizations that we interviewed consider the process of authorizing an action after a decision to be almost identical with making the decision itself, the reduction of organizational levels involved in decision making with the use of predictive analytics also means that there is a decrease in the number of levels involved in authorizing actions. The findings are consistent among all the companies that we interviewed and in line with proposition 7 of Huber's theory (Huber, 1990).

Regarding the findings that we obtained when assessing the influence of predictive analytics on the number of nodes in the information-processing network in the organizations, the results have a uniform distribution in terms of respondents' opinions. Half of the respondents (three out of six) perceive that the use of predictive analytics helps their organizations to reduce the number of nodes in the information-processing network since the employees are able to access the needed information (prediction) on the demand. The other half has the complete opposite opinion arguing that the predictive analytics provides them with rather complex information that needs to be processed by multiple employees or departments so that a final decision can be reached. These inconsistencies make it impossible for us to generalize the findings and point out towards a need for further research to be done by academia or practitioners to investigate the circumstances in greater detail.

Effects on organizational memory

We examined the effects that the use of predictive analytics has on organizational memory using the variables of development and use of data bases and development and use of in-house expert systems, according to Huber's theory (Huber, 1990). Regarding the development and use of data bases our findings are consistent and similar among all the companies we had an interview with. The predictive analytics stimulates the growth of data for them and they perceive the more frequent development and use of data bases as components of organisational memory as something that is unavoidable. The use of predictive analytics leads to more frequent development and use of data bases which is in line with the theory from Huber (1990).

When analyzing the influence from predictive analytics on the development and use of in-house expert systems as components of organizational memory, with relation to the existing procedures for development and use of the expert systems, our findings were mostly consistent with four out of five responses that are in line with Huber's theory (Huber, 1990). That means that most of the organizations perceive the use of predictive analytics to be demanding for more user friendly procedure for development and use of organizational memory components. That also leads to more frequent development and use of memory components which purpose is to support the decision making in the organization. There is misalignment only at the company C-Retail and the reason for that might be that so far their procedures for development and use of organizational memories were in line with organizational demands so no changes have been trigged so far by the use of predictive analytics.

Effects on organizational intelligence and decision making

In accordance with Huber's theory (Huber, 1990), the effects that the predictive analytics has on the organizational intelligence and decision making are assessed using the following variables: effectiveness of environmental scanning, quality and timeliness of organizational intelligence, quality of decisions and speed of decision making. The analysis of our empirical data shows that the use of predictive analytics leads to scanning of the environment with increased effectiveness. Our findings are consistent for all of the companies that we interviewed showing that the use of predictive analytics leads to more rapid and accurate identification of problems and opportunities which is in line with Huber's propositions no. 10 (Huber, 1990). It is important to notice here that the interviewees from every company were able to provide numerous examples and cases that despite confirming the propositions, show rich details about the importance of the predictive analytics as a unique resource for understanding the environment the companies act in.

Similarly to the findings we obtained when assessing the effectiveness of environmental scanning, the results from our analysis of the quality and timeliness of the organizational intelligence related to predictive analytics show consistency across every company that we interviewed. The companies heavily rely on the intelligence they get from the use of predictive analytics in a timely manner. Numerous indicators points out to the high perceived accuracy, comprehensiveness, timeliness and availability of the organizational intelligence which is a result from the use of predictive analytics. Since the organizational intelligence is the input in the decision-making process in an organization (March, 1999; Huber, 1990; Sammon et al., 1984), the effects on quality and timeliness of the organizational intelligence directly reflect in the same way on the decision-making process.

In addition to that, it is logical to say that an increased quality of organizational intelligence leads to making decisions with higher quality. Companies associate the use of predictive analytics with means for optimization, expansion and growth of the business, building and testing scenarios for multiple purposes and assessing the outcomes, and as a resource that supports them into making more informed decisions. The quality of the decisions that the companies make based on the use of predictive analytics is unanimously perceived to be increasing, which is in line with proposition no. 12 of Huber's theory (Huber, 1990).

Finally, the last examined variable is the speed of decision making which is assessed through the time needed for making decisions and the time needed for authorization of proposed actions. We must state, in our analysis we found that the process of authorizing actions was identified to be the same with making decisions among all companies, as the authorization is perceived to follow naturally when a certain decision is being made. The majority of the companies that we had an interview with, perceive the use of predictive analytics to be reducing the time required for a decision to be made (and the time for authorization of actions accordingly) which is in line with propositions no. 13 and 14 of Huber's theory (Huber, 1990). Only one company, T-Mobile, stands out by arguing that the use of predictive analytics in fact slows down the decision-making process. The interviewee considers the constant growth of the available data and the need for analyzing it, while arguing that their company trades the time need for decisions to be made for increased quality of decisions themselves. Possible reasons for the fact that the findings for T-Mobile differ from the others could be greater IT maturity, difference in the ways predictive analytics is used or differences in the IT systems (tools) that they use.

6 Conclusions

The objective of our study was to generate knowledge about the perceived effects of the use of predictive analytics on decision making in organization and thus contribute to IS research. To achieve that, we conducted a qualitative study examining organizations that use predictive analytics to support their decision-making processes, for the purpose of answering our research question:

What are the perceived effects of the use of predictive analytics on decision making in organizations?

We answer our research question by analysing the perceived effects of predictive analytics on decision making through the scope of Simon's model of the decision-making process (Simon, 1977) and by testing the propositions of Huber's theory of the effects of the use of advance information technologies on organizational design, intelligence and decision making (Huber, 1990), in the context of predictive analytics as an advanced information technology.

Regarding the perceived effects of the use of predictive analytics in the organizations, analysed through the prism of the Simon's model (Simon, 1977), our study reveals that the predictive analytics supports the intelligence and the design phase of the decision-making process, but does not have an effect on the choice phase. The use of predictive analytics helps organizations to get a better understanding of the environment that surrounds them, discover problems or new opportunities, define decision criteria and also stimulates the information gathering and sharing in the organizations, as activities related with the intelligence phase. In addition to that, the predictive analytics assists the organization in the activities of development, evaluation, comparison and prioritizing scenarios as possible courses of action in the decision-making process, as part of the design phase. Furthermore, we find that the predictive analytics is not perceived to be affecting the choice phase of the decision-making process and the decision makers are always the ones that have the final word when it comes to selecting the alternative as a final decision.

Hereby we present the findings of our study related to the perceived effects of predictive analytics on organizational intelligence and decision making, in accordance with Huber's theory (Huber, 1990):

- *Effects of predictive analytics at subunit level:* The use of predictive analytics is perceived to influence the participation in decision making in terms of increasing the number and variety of people that participate as information sources in the decision making in the organizations. In addition to that, it can be stated that in general, the predictive analytics is perceived to affect the size and heterogeneity of decision units in the organizations by reducing the number and variety of people that comprise the decision units.
- *Effects of predictive analytics at the organizational level:* When discussing from a perspective of the whole organization, the use of predictive analytics is perceived to be helping decentralize the decision-making process in centralized organizations, by ena-

bling people from lower hierarchical levels to make and authorize decisions with a satisfactory level for the organization. Furthermore, the use of predictive analytics is perceived to be reducing the number of organizational levels involved in authorization for actions related do a certain made decision.
- *Effects on organizational memory:* The use of predictive analytics is perceived to trig more frequent development and use of organizational memory components and by doing so, it affects the decision-making process by providing better information in terms of quantity, quality and timeliness. Additionally, the predictive analytics stimulates the organizations to update their procedures for development and use of organizational memory components, which also leads to more frequent development and use of organizational memory components.
- *Effects on organizational intelligence and decision making:* The use of predictive analytics leads to more effective environmental scanning for the organizations, in terms of providing means for faster and more accurate identification of problems and opportunities. In addition to that, the predictive analytics increases the quality, timeliness and availability of organizational intelligence which is used when making decisions. Furthermore, the use of predictive analytics increases the speed of decision making in terms of reducing the time needed for a decision and authorization for actions to be made. Finally, the strongest and the most important perceived effect for the organizations is that the use of predictive analytics leads to large increase of the quality of the decisions that are made. The predictive analytics is considered a unique resource, something that gives the organization a competitive advantage on the market by increasing the quality of the decisions they make.

When testing the propositions of Huber's theory in the organizations we encountered two inconsistencies which drew our attention and therefore we want to express the need for further research in order for conclusions to be made out of them. First, when assessing the perceived effects at subunit level, opinions are divided when discussing the influence the predictive analytics has on the organizational time consumed on meetings related to decision making. Additionally, the second inconsistency is related to the perceived effect of predictive analytics at organizational level, in terms of the influence predictive analytics has on the number of intermediate nodes within the organizational information-processing network. The number of information-processing nodes directly affects the speed and the quality of the decision-making process in the organizations and hope that we presented motivation for future research of the effect that predictive analytics has on it.

The predictive analytics is considered to have a vital meaning for the decision-making process in the organizations. Whether they need to predict the customers behaviour, market movements, sales in order to offer the right products to the right customers in the right time, target the right customers, launch a new marketing campaign or engage new markets, organizations feel that the predictive analytics is a unique resource that gives them competitive advantage, which is of crucial importance in their decision-making processes. Despite all that, even though organizations know how important predictive analytics is for their decision-making processes, we find that it is not the only thing they rely on when decisions are being made. Great value lies in decision makers' experience as well as in trying out new ideas that organizations can have and new events that they may create, without having the opportunity to predict their success because of lack of historical data. The decision-making process in organizations does not depend solely on predictive analytics, but it is rather complimented it in a very significant way.

Appendix A: Interview guide

Introduction

1. What is your position in your company and what is your role?
2. What types of decisions are you required to make?
3. How do you make those decisions (tools, feeling, meetings etc)
4. How do you use predictive analytics? In what form (program, software, system, only running various algorithms/queries)?

Effects on organizational intelligence and decision making

1. Does predictive analytics help you discover new opportunities?
2. What are the effects the use of predictive analytics on the organizational knowledge?
    a. Is knowledge generated more quickly?
    b. Is the quality of the knowledge increased?
3. How do you evaluate the outcomes of the decisions made based on predictive analytics?
4. How do you think predictive analytics affects the time required to make decisions in your organization?
5. How do you think predictive analytics affects the time required to authorize actions in your organization?

Intelligence phase

1. Do you obtain more data using predictive analytics?
    a. What do you think of the quality of that data?
    b. Is the amount of data growing fast?
    c. Is there any other way to get that type of data?
2. Does predictive analytics help you notice any patterns or abnormalities in customer behaviour?
    a. Have those patterns been proven as valid, correct to some extent?
3. Do you make any categorization of your customers according to their behaviour, based on the information you get using predictive analytics?

Design phase

1. Does predictive analytics provide you with different options from which you then choose to make a decision?
    a. Can you give an example of a type of decision made like that?
    b. Does predictive analytics help you predict the outcomes of the offered alternatives or create scenarios?

Choice phase

1. How do you choose the best alternative when making a decision?
    a. Does predictive analytics have any part in making a choice for you?
2. Do you rely on predictive analytics to make a decision excluding any human factor?
    a. What do you think of the role of a human factor in the process of making a choice?

Effects on organizational memory

1. Does the use of predictive analytics implied making changes in your procedures related to development of knowledge repositories?
    a. Do those procedures support more frequent development of knowledge repositories?

Effect from the use of predictive analytics at subunit level

1. With the use of predictive analytics, do you think there are fewer or more people that generate knowledge which is used for making decisions?
2. With the use of predictive analytics, can people from different departments and backgrounds generate knowledge for making decision?
3. With the use of predictive analytics, do you think there are fewer or more people required for a decision to be made?
4. With the use of predictive analytics, are people from different departments and backgrounds enabled to make decisions?
5. Do you think meetings now last more or less, using information based on predictive analytics?
6. Considering the use of predictive analytics, do you need to have meetings now more often, compared to a case when you don't use it?

Effect from the use of predictive analytics at organizational level

1. Do you think that the use of predictive analytics allows people from different levels in hierarchy to make decisions?
2. How do you evaluate the quality of decisions being made at lower hierarchical level with aid of predictive analytics?
3. Once you have come up with a decision based on predictive analytics, do you need to get an approval from your superiors in order to authorize an action?
    a. If so, how many levels does that information travel through?
    b. What would it be like if predictive analytics was not used?

4. Considering the use of predictive analytics, are you required to communicate more and more frequently with colleagues from your department in order to make a decision?
5. Considering the use of predictive analytics, are you required to communicate more and more frequently with colleagues from different departments in order to make a decision?

Debriefing

1. What is your general impression of the use of predictive analytics in terms of decision making?
2. Are there any problems that you would associate with the use of predictive analytics as a mean to support decision making?
3. Is there anything else that you would like to add, some aspects that you think we missed or other things to point out?

Appendix B: Transcript T-Mobile

B – Bojan
D – Mr. Dimitar Marinovski

B: Thank you very much for this interview today. First of all, I'd like to ask you, what is your position in the company and what is your role?

D: My position is Director of Marketing Intelligence and Market Planning, so my role is to collect valuable data from all marketing aspects, to make that data available in a transparent and digestible way for the top management, and then to influence, to steer and to have an input in the business decision that would be made in a certain time period.

B: What types of decisions are you required to make?

D: Generally there are not many decisions that are directly coming from me. It is more like the areas that are directly influencing, and that are subjects for my decisions, mostly related to the budget spent in order to collect certain type of market information, specifically in this case, budget for marketing researches. The other types of decisions are also ... I will not call them decisions, they are more like proposals bottom up, forecasts bottom up, suggestions bottom up, reports that are going to the top management . At the end of the day, the decision that is going to be made, it will not depend solely on me. It will be brought after the management is aware of this certain step, or the certain output that we are looking, and usually I am not bringing direct decisions.

B: How do you usually make those decisions? Do you use any tools, or do you rely mainly on data, or is it your gut feeling that you use mainly?

D: In my job we try to eliminate the gut feeling to the maximum. Whatever claim, conclusion or trend we are suggesting or showing, it has to be as much as possible, based on the real facts. Ideally, we like to eliminate the gut feeling totally, but in the business this is almost impossible.

B: In what form do you use predictive analytics in your organization? By predictive analytics I mean data mining or any sort of tools to predict certain behaviour or events, based on data from the past?

D: This is very wide area that you have touched. We are using predictive analyzing in many different aspects. Usually when people mention predictive analytics, first that occur to my mind, are for example, predictions about the customer behaviour. In this case I would more concretely look at the predictive term analytics that we are preparing regularly and we do this in order to influence and to try act preventively, in order to stop the turning of our customers toward competition. But this is only a small part. We have many of this type of actions. I will say that even the forecasts and plans that are prepared for the long term development of the business plans of the company, are based on some sort of predictive modelling.

B: Can you tell me, does predictive analytics help you discover new opportunities?

D: Absolutely, yes, I would say 100% percent.

B: How do you describe the effects of predictive analytics on organizational knowledge that you create here (in the company) and store? Is it generated more quickly maybe, or is the quality of knowledge increased by the use of predictive analytics?

D: Well, as in all other things, it is best if you do the things step by step. Usually when we introduce a new process that is based on some sort of information, that is based on predictive analytics, we usually never fully rely on that, until we first verify whether this is really reliable, whether the method, the data, the outcome, actions that we anticipate with this are enough reliable to be used as a standard business tool. So usually in this part of the process we first initially collect some type of information, we process it, we make some conclusions based on it and then we have to pass some certain test period in which we will verify that what we were saying with this is really becoming a reality. For example, I mentioned the case of the turn prediction model. In this model, based on the past behaviour of specific groups of customers, we try to predict which types of customers are most vulnerable in the next period. And for sure in this process, after some period, we make comparison how much is this tool bringing better results than if we would only randomly picked the customers for the chart (poll). Let me make it more concrete, maybe we will come to that later in the questions, because I don't know what is coming. Just to make it more transparent, even if you try to say, the most simple tool to do this type of exercise would be that you try and pick random customers and there is always small percent of probability that you will pick (*the right ones*). So the model we are building in order to do turn prevention is a compare to the general probability that you will pick, and there is a certain rate. After that is showing whether the overall model succeeded. Until the model is brought to a certain success level, it is not wise to use it because it is not giving additional value and every type of data analytics is requiring resources, investments and money, requiring certain time. So if this model is not proven, verified that is bringing value, it may go into contradiction and bring unreliable result than if you would not use it.

B: So the next question is connected to this one. How do you evaluate the outcomes of the decisions based on predictive analytics, and you mentioned the testing. Generally speaking, with those decisions, do you have positive result or negative outcome or you cannot generalize that?

D: Generally it is difficult to say, it's like having a lake and then you try to empty the lake with a bucket of water, but there is an additional river that is filling the lake. What I would say, predictive analytics is always helping the business, but it is not the master tool that will drive the business. Otherwise, if the business was driven only by predictive analytics, mathematicians would be the best businessman in the world. So it is a strong tool to support the business, strong tool that contributes to making decisions, but it cannot steer the business totally. In the business you have much more important factors. The management has to have visions where the company should go, in which direction. It has to have some solid power, some solid energy, some solid determination to bring the company there. And all this type of tools that are especially good when you are speaking about optimizing your business, are without any doubt very valuable, but these are not the only tools that are used to steer the business. Again, I will never underestimate the power of ideas of bringing something totally new in the business, for which there was no prior record, there is no prior trace in the data. I think this is the real generator on how you can grow the business.

B: Can you tell me how does PA affect the time required to make decisions? Is it slowing you down maybe, or does it help you go faster to make a decision?

D: Well, I can say for sure, if you collect more data and you take more information into account when you make decision, it obviously means that you will spend more time. So it will obviously slow you down in decision bringing. But the uncertainty in the period of making decisions is much lower. So again I would say it is always a trade off. You cannot make all the possible analysis and then make decisions. But it would be stupid to make decisions without any backgrounds, without any analytics and any analyze behind that. So it is always a trade off. Sometime you have to act quickly to bring decisions for which you don't have time to make proper assessment, proper analytics and in that case you are taking certain risks. You have to be aware that there is a risk, but you have to bring that decision quickly.

B: How does it (predictive analytics) affect the time required to authorize actions?

D: I think is… I don't know if it makes any difference in the time to authorize the action, because usually, once we make a decision, it goes together with the actions that consequence that decision. So it is the question to make certain judgment, a certain choice. Once you do the choice in the normally working company, there should not be any more time necessary to bring the actions.

B: Do you obtain more data using predictive analytics compared to the case when you don't user predictive analytics?

D: Predictive analytics is based on data. So we are processing tones of data as I am in this company more than 20 years. The amount of data that is being processed is increased and Ii think it's not the only case in this company, it's a world trend. The people have discovered that, by processing data you can add some value to the business. Since then, this has become major trend worldwide. Because obviously as the world becomes one single market and the competition is getting bigger and bigger, the companies that are having better information, better understandings of its customers, more data about their customers and I will say here not just more data, but more data processed in a meaningful way, this is more important , these are the companies that have better chance to survive and this will not stop here obviously, not even after 30 years and every single data that we are generating, moving, eating, watching movies, will be processed by somebody, giving it a meaning of a business opportunity. I mean the operators that are producing our homes have big advantage because they are collecting the GPS data, they are doing some analytics based on this, they are improving their services based on this ... this is never ending story and I don't think that this will decrease, this will only increase over time.

B: Do you think there is another way to collect that kind of data that you are using predictive analytics to collect, or is it a sort of unique resource that you use for your company?

D: Well I think that every company has a specific in its own business and company should be the best player that could collect own valuable data. Ok this may be different in different industries. It is not very wise to make general group for all industries. There are some industries in which the companies are having the most of the data for the customer and for the potential customers. There are some industries in which companies are not having at all data of their prospect customers so they have to collect on other resources, other sources of information. And finally, at the end of the day, that companies that have anticipated this value of data, they have created business on its own by collecting and selling this type of data . I mean Facebook is the example how companies can live on collecting and selling, making business only from the data of its customers. And Google as well.

B: You mentioned previously you detect patterns of customers' behaviour, are they proven to be valid so far most of the times, based on the sales that you've made toward them or other criteria?

D: Yes. I would say. As I mentioned for example for the turn prediction model, we can easily compare how good this model in which we select some group of customers is. Then we say ok, within this group there is much higher probability that the customer will turn, than if we randomly pick the same amount of customers. For example the model gives out... I don't know ... lets' say 100 customers and in this we can find 10 customers that will turn. While in all customers basic, we pick 100 customers randomly, this will get only 2 customers to turn in reality. So in this cases it is easy to see that we are having this type of results we are continually measuring the success of the whole mechanism. It is not only the data processing, but how we address later those disclosures and we believe that we can easily prove that it works.

B: Those multiple scenarios that you've mentioned. Does predictive analytics give you different alternatives that you can choose and you can maybe determine the probable outcomes of certain scenario and you choose maybe the best of them?

D: Yes that is also the case that I mentioned. For example, when making the market model of the overall market, we can test and make different types of scenarios to see which one is the most valuable for us. We can make different type of assumptions what will happen on the market in the next 5 years. Then we see what would be the role of the major players on the market. What are the likely actions in terms of the event that something goes in one or another direction. And then we make choice based on this, because we say ok that is not the scenario that we like, this is the scenario we would like to push for. So this is the way how you can make prediction. You have to. All the decisions at the end of the day, based not only on qualitative thinking, what we think would be better, but also with how much would be the difference. So it needs to be quantified. In the moment you sit to quantify something, you immediately notice that you need a sort of data and analytics. Even when you need to launch new products there is always impact that you're going to do for new customers, also for existing customers and you start with, basically building a case, based on some sort of data that you collect. So I think that collection of data and analytical processing of data is build in every single action that is done in the modern business.

B: And the choice of scenario is done by human factor and not automated?

D: Yes that is always the case.

B: With the use of PA do you think that there are fewer or more people that generate knowledge for making decisions? People that will be considered as information sources, maybe they use the programs and then they analyze data and report to higher structures in the hierarchy of the company?

D: I think in order to come to certain business conclusion you are usually starting the data inquiry with some sort of ideas you have in your mind. So you would like to prove that something is happening on the market. Maybe for example, I would like to prove that sale is slowing down on the overall market. Obviously I know my sales numbers, but I don't know the sales number of the competition. And then I start thinking how I could find the sales number of the competitors. And then you try to get some indirect sources on data to collect this, to prepare and present it, in order to bring some other types of business decision. What I am saying is that, data mining, I don't know, will it reduce or will it increase the number of people? I think it will increase the number of people that need to collect the data. On the other hand the tools that this people are having new IT capabilities to process the data which is increasing all the time. This is a kind of tool with different mechanisms, one is asking for less people and the other one is asking for more people. What is the output, I think it is pretty much dependant of the industry where you are working. If you have limited source of data all you have to do is to process the amount of data that is increasing. Probably, at the end of the day you will need less people. On the other hand if you need to collect data from much more sources and this is always growing and increasing and you need to think always to find your different sources of information, this might lead to increase of people. I am not sure what the impact is. I know for sure, we had much less people 10 years ago, working on data analytics than we have today.

B: What do you think about the communication between different departments with the use of the predictive analytics, is it facilitating the communications, are you required to communicate more with different departments with IT maybe or with sales?

D: Yes absolutely. In past years there is a huge transformation of IT, generally moving much closer to the customer of their own report, we're the business parties customer of the reports and there are much more developed, not only links, but tools how that end users will make customized type of report to customized type of requests to IT. And I think this communication is increasing constantly, even the data warehouse we've introduced is having direct end user interface that can provide many types of reports on their own without a need to involve IT. So in the past years it was always IT person that was used as an interface between marketing and systems, this is where the data was, so he had to understand what the other persons are asking. Then he had to translate into something that is understandable for the data warehouses and in the few iterations to come to the desired report. Nowadays there are practically many cases done directly by marketing, directly accessing, directly extracting, then checking why the report is not giving what they would expect, then clarifying what is it about, is it about data is it about quality of data, or is it about something else that is going wrong in the real world different than the expectations.

B: What do you think is the influence on meetings that you do to make decisions from PA? Is it reducing or increasing the time you spent on meetings to make a decision, are meetings more frequent now or less frequent?

D: I would say there are two things here important. First, the processing and the pre-processing, the preparation of the analytics is obviously giving better view to the top management and better answer for all questions that you need to have in mind. But as the available data and reports are growing, the management becomes more aware of this and is asking all the time for more. So I would say this is again some sort of never ending story the way you more present the data in more digestible way there is always new ideas on the aspects that have not been considered before, because it was too far to think about that. So if today... I don’t know ... if you are aware today... lets simplify. If you were aware today that you can have weekly reports and you can have all the sales, all the turns, all the revenues on weekly day, then the next thing you will come up as a request will be to have it on daily bases. I mean that's a simple example that is repeated not only with time direction, but also in other dimensions to go the level of city, to go to level of community, to go to the level of single customer. The hunger for data is growing all the time. As I said 10-20 years ago it was minor part of the business, today it is significant part of the daily operations.

B: Do you think with the use of predictive analytics different hierarchical levels can make decision more easily?

D: Yes. Absolutely. Some of the processes, as I said, that are going in the same direction, once you understand that some process are firstly introduced then proved that they will bring value then you introduce them, it is a focus for some time until you verify that is producing the predetermined results. Then it is simply put down to a lower level of decisions because there is no….. because the development of the company, decisions that are coming to the upper management levels, don't need to decide for something that is becoming standard operational practice. That is just continuing to be complete steered in lower managerial levels. And there is only getting some sort of KPIs, that with time flow, are becoming more and more, but then you merge them into one KPI and then group certain categories, because the time is always limited, and quantitative data and the number of decision is constantly increasing.

B: And they keep the quality of decisions that are being made on lower level satisfactory?

D: Yes. Because once you establish the rules there is not much to risk and not much to think why this should not be decided in the lower level. In fact everything that could be decided in the lower level is referred that it is decided in the lower level. The only thing that you need to do is to limit the risk. The only thing you need to know is that the processes is with some sort of frames that have been already agreed on higher level. After that you don't need to control the process.

B: And it is the same case with authorization?

D: Yes. It is completely the same

B: What is the general impression of PA in decision making? Is it good experience is it something that you wouldn't replace in the following years? Do you see any potential for improvement there or anything that should be done in terms of algorithms, tools and programs?

D: What I will say again. I think it's here and it is not going to disappear. It's going to grow further. Always as always, I would highlight, before you go into some sort of detailed data processing, it is very important to have clear idea for what purpose you are doing it, and at the end of the day, this purpose needs to be reflected on the business. So in that case you are doing this correctly . If you are collecting data, processing it without any tangible use or cannot prove that is bringing value to your business I would say don't do it . It is like a thing that you do just because all the people are doing it. No this is not the right thing to do. The successful companies are the ones that are always able to optimize between their costs , their resources spending , profits, and the revenue that they are generating . So I would say yes. 100/% predictive modelling, data mining will only grow . But I would say they always have to be done in sense that is driving the business needs of the company. We want to go in certain direction we want to investigate. If we can prove in some time that this process is collecting data, the process of spending resources is bringing another value, then we should continue . If not we should stop and focus the resources on another subject .But anyway this cannot be avoided.

B: Is there anything that you want to add?

D: No. These are basically my thoughts.

Appendix C: Transcript DBank

B – Bojan
M – Chief Retail Officer at DBank
S – Department Manager of Card-products at DBank

B: Ok, thank you very much for your time. I'd like to ask you what is your position in the company, what is your role, what are your responsibilities?

S: I am covering the business area as department manager of the card - products, my name is [redacted].

B: And what do you do mainly what are your responsibilities?

S: My responsibilities are mainly covering the portfolio of credit cards of the bank, propositions following the profitability of portfolio and everything else that has to do with portfolio management, considering card business of the bank.

M: Ok my name is [redacted], chief retail officer, so I'm covering the whole area of retail, management of the products, branch network and all other alternative challenges.

B: And what kind of decisions are you required to make on your daily agenda, are you bringing strategic decisions mainly or are they operative decisions?

S: Decisions are always a part of some process, so there is a decision-making process, it's not an individual or a person that makes the decisions solely on his own, so mainly we are involved in analyzing solutions and proposing decisions that are going to or entering actually an approval process. So within our daily work we are following market situations, portfolio performances, following a lot of key performance indicators, which have to be aligned with our business objectives for the current year, then proposing solutions, measures, or actually activities that should support our business objectives for the current year.

B: Are this all types of decisions that you are required to make?

M: Ok this is very common but quite difficult question because the strategic ones are of course discussed upfront we have a process of reaching the common ground of understanding, somehow deciding what to undertake, but the most important thing is that, once you do something, let's say, decide that this is the best one, you have to, quite on a frequent base do the follow up and see whether the decision that you've made at that point of time is quite reasonable and appropriate, whether is actually happening in the real life on a day to day basis, and as far as the rest of decisions are concerned there are plenty of them on a daily basis, but I wouldn't say that they are the strategic ones, but sometimes, you know, it is more important to make the decisions, even though some of them are not the right ones, but it's still better to bring the decisions and to leave them like they are, so that would be in general.

B: How do you make your decisions? Do you rely on data mainly or do you use any tools or software or is it the gut feeling that you use on making decisions?

S: Well every decision contains a little bit of everything that you've previously mentioned. Of course we are basing our decisions or proposals for certain decisions on available data, tools. We are also dominantly involved in data mining and analyzing a big set of data, characteristics and performances of our customers, trying to segment customers in different sub-segments in order to identify customers that are underperforming and identifying customers that are performing better, in order to stimulate them additionally.

B: And you how do you make your decisions?

M: Yes, actually, what we do, it's again, interrelated with the previous answer. No matter whether you have more or less elements to make the right decision, what we are trying and aiming to do is on a much smaller scale, in order to test it and to see what is the outcome actually. And if we see that, because some of them are, let's say brilliant, it proves to be that some of them are completely not appropriate, we do not use any sophisticated models, but even if you have one, I suppose the best approach is to do it on a smaller scale to test it and see it and then to go, let's say, maybe on a larger scale only then when you see really proven results, the ones that you've expect them to be, so more or less, again we wait mainly for the outcome data.

B: Is predictive analytics helping you to discover new opportunities?

S: The analytics are crucial for portfolio management. As I said before, they are crucial for identifying sub segments of our portfolio, identifying new opportunities, identifying which customers are eligible for offering new products, which customers are eligible for offering more matured products, or which customers are maybe showing behaviour that is risky for us or other perspective behaviour that is sending signals to us that customers are using less our services and maybe using the services of some other bank. We do that in order to have a timely approach towards those customers with some proposal and probably make some offer in order to attain over customers and make them closer to average performance.

B: How do you think predictive analytics influences the organizational knowledge that the company generates about the customers or anything else? Do you think that the quality of the knowledge is increased, or is knowledge generating faster to say?

S: Well, the data that we receive from the behaviour of our customers it's important for the overall knowledge that the bank accumulates, afterwards, how this knowledge is utilized in order to create the strategy for the future. And yes, we definitely generate more knowledge, knowledge with high quality. For instance, the predictive analytics can quickly show us what are the preferences of young customers, how the bank has to restructure its products and offerings in order to create something that will match the needs of new customers, especially the young customers as an example.

B: How would you evaluate the decisions making based on the analytics? Are customers responding well according to analytics or to packages that you structure to sell?

M: I don't think that we can talk of something that could be measured right now, especially if we think for, let's say, tailor made customers' products and services. But what is very important the traffic that is coming on daily basis is somehow incorporated in whatever it is, let's say as a knowledge or data that would come, because the things are changing quite fast. Faster than we think that is going on. And how we can actually take the advantage of all those inflow through the traffic, through different channels, because mainly it's prevailing the branch network and this is for sure for the country like Macedonia. The things are happening quite faster, and if we are able to get along the way in appropriate timing, to meet this, especially digital native clients that are coming, although we think that is far but it's not, then we think that we can really adjust to whatever it is coming and be able to take this challenge as an opportunity not as a threat.

B: You analyze the data, you make some decisions based on that, and those decisions bring some actions after that, and those actions, are they good most of the time, is the response satisfactory for the bank?

S: Well, as [redacted] said, we usually first perform test on a smaller samples in order to analyze the results of the action. We take on the sections from the portfolio and if the results are satisfactory that is a green light for the proceeding with those activities toward the whole portfolio segments.

B: How do you think predictive analytics affects the time required for you to make a decision? Is it speeding it up or maybe slowing you down because all of the data that you have to analyze in order to make a certain decision?

Well, it's actually a question of whether you have arguments, or you don't have arguments for making the decision. You simply have to pass the despair path of making some analytical work, especially in the banking in order to know that your decisions will result with appropriate action. If you make decisions that are not based on some analytics that you performed on portfolios, you risk actually the outcome of those decisions. Still, with predictive analytics we eliminate speculations and we are able to reach a decision way faster.

B: Is it the same case when it comes to authorizing actions for the decisions you made?

M: The authorization of actions comes naturally with the making of decisions. What I'm trying to say is, once we have assessed a situation, analyzed it, reached certain conclusions and made a decision – the authorization of actions comes automatically with the decisions.

B: When you use predictive analytics do you obtain and generate more data, compared to 10 years ago, let's say?

S: Well, yes. Analytics have this in their nature. Whoever is dealing with analytics can tell you that their initial results are giving you only the trigger for additional analyzing. So the initial results from analytics are actually only indicators for what you need to perform as a new data mining in order to come to a point where you will see what the necessary decisions you have to make are, or actions you have to undertake.

M: This is very important what [redacted] is saying and it happens to us very often. You start doing something, you do not have everything in front of you, you don't have a guide that will perfectly lead you through the forest. And then, as long as you get some data, you realize that, if you think proactively, you need additional more and additional more to round up whatever you like to identify and afterwards undertake the actions. And from that perspective, as you mentioned before, even the growing of the knowledge is coming automatically, it's actually demanding to do it - if you like to do it the right way.

B: Did the predictive analytics demand changes in the procedures and ways you store and manage data, developing data warehouses or expert systems?

S: Well, I think with the expansion of data, of quantity of the data that we analyze and make predictions, we had to adapt to the new circumstances. So yes, we had to somewhat adjust the procedures for development of data warehouse so that everything goes more, smooth to say, more flexible. Actually, that way we eliminated some steps and ensured more efficient work.

B: Are you building different scenarios with predictive analytics and measuring outcomes from those scenarios and then selecting the best scenario when making a decision? How does that work?

S: Yes. But it depends, because with every decision you are coming to a point, where there are different scenario options. Usually we have this basic approach of most optimistic and worst case scenario taken in consideration. Most usually we adopt something that is in the middle before making a decision and undertaking action. But before making a decision you should always consider the worst case scenario as an basic approach in order to consider what is the worst that can happen undertake measures and also what is the worst thing that can happen if you wouldn't do anything.

B: How do you choose the best scenario is it a person that is choosing or the system maybe recommends the best alternatives, or is it both of them or maybe a combination?

S: At this moment it's a combination. But mainly human on the basis of available data. Human, but not only one individual it's really a combination of those that are somehow part of the strategy sector. Human always makes the decision but before that we are preparing this scenario, sometimes we consult the system, what results will the system give us treating them as some possibilities and outcomes. But we are still in the phase where we are not using already - made model, so we prepare them on our own, combining different analytical data.

B: Do you think that more people are acting now as information sources for you to make the decisions based on use of predictive analytics? Are more employees using it and becoming information sources in order for you to make a decision or you don't think so?

S: Well, in this era that we are now living, are actually more working places in the bank industry in different departments which are based on analyzing analytical data from the system. So we can say that most of the people that are being consulted for making decisions are involved in data analyzing within their scope of activities. Yes but not on a larger scale with regular employees.

B: Do you think that more people are required for a decision to be made or not, considering the use of predictive analytics?

S: More people are required in the process of coming to the stage when you are in position to make a decision, so more and more people are involved during this process. The decisions are never being made by intuition, at least in the banking industry. The result of the analysis is performed by usually more than one division of the department. We need more people, different people, to be sure that they made a decision which is as good as possible.

B: How do you think the use of predictive analytics affects the time spend on meetings and the frequency that you have on meetings in order to make a decision?

S: Well it affects it. It is time consuming process, but everyone has to develop the skill on how to present the main points from the analytics, because in many occasions analytics can create a confusion if they are not interpreted correctly, or not summarized correctly it can create a chaos and you will not know what is the right decision to make. The interpretation of analytics, especially from the managers starting from the lower level up to the senior level is actually crucial in the whole process. Not summarized analytics or miss-interpreted analytics will often guide to a process of never making a decision or it will make the decision process very difficult and never ending. I think there is a big room for improvement on the time we spend on the meetings, as you say, that are related with predictive analytics.

B: Do people from the lower hierarchical levels can make good decisions with the use of predictive analytics, good decisions for the company i.e. with satisfactory results?

S: Yes, people are involved in making decisions in everyday processes of banking even starting from the branch. Predictive analytics is also used even on a single customer level. When a customer comes to the branch and wants to have one product, then to a branch employee, performs some very basic analytics of the customer day time activity behaviour in order to see the potentials or needs for using certain banking products and approach towards the customer by certain set of offerings.

B: How do you think the use of predictive analytics influences the communication among the employees from one department and between departments, are they required to communicate more frequently?

S: They are required to share experience. This is very important to share experience to share knowledge actually, especially among middle level of management, in order to combine the knowledge that is gathered within certain departments. For instance it is very important to have predictive analytics that is coming from marketing campaigns to know how different marketing approaches are actually contributing for certain promotions or certain product campaigns.

B: And then they share with other departments as well, department of sales, retail, and so on?

S: Yes, of course, in order when the new decision is being made, they can utilize the knowledge base from the previous campaign or decisions.

B: We are slowly reaching the end of this talk. I'd like to ask you what is your general impression of the use of predictive analytics and maybe some assumptions for the future would it be more developing in the future? Do you think that will appropriate more advanced solutions and as well as other companies?

S: Definitely it is something that is.... we are living in a time when predictive analytics is a necessity to be used on a daily operational level and a process for decision making at any level. So working in this kind of environment definitely makes it necessary to make some analytical work before making any decision. The future is bright for predictive analytics, but in our case it will probably be a development in creating new models and probably in predictive analytics there will be some well known models in the future for different industries and for different portfolios of businesses.

M: Ok, I think we should be aiming to a phase where this will be nearly getting much more of importance. To be ready somehow through whatever access client is doing to the bank to be able to have ready offer according to the behaviour, according to the past experience and what so ever is gathered within the bank. Reaching that stage we know that we have also other phases that need to be completed, but it is something on which we are in serious considering and we like to put a lot of effort in order to offer on-time product, when the customers, let's say are approaching us from different types of channels or to be able, let's say, right now is just a theory to be able to offer something that will not be as we do right now mass marketing, but to be you know permission based during the process of accessing the bank, so this is our aim. But we know that for this stage we have to have a walk for a little bit more and a little bit faster reaching that stage.

B: Do you see any problems with the use of predictive analytics?

M: From this perspective not really, because we cannot say that we have experienced everything in terms of a model of a.... maybe the phases will come but I think that if we continue doing it, of course again not to make a bigger mistake gradually... and carefully with a close monitoring I think that whatever comes should be handled just in time with appearing to be aware and to adjust accordingly and quite faster in order not to create any damage. We hope to be moving towards that direction taking advantage of the situations.

B: Thank you very much for your time.

Appendix D: Transcript One

B – Bojan
M – Ms Marija Mirkovik

B: All right, so thank you very much for this interview today. I'd like you to ask you, what is your position in the company and what is your role?

M: I currently work at the commercial analysis specialist within the Finance department and I work with everyday data that depict the customers their usage and the revenues they generate.

B: And what types of decisions are you required to make?

M: Usually the decision-making process in our company is limited to the management. I only provide the different inputs to support that decision decisive process. So I think that my personal decisions are based on what type of data I am going to use the way I am going to present it in a most effective way so they could contribute to the decision making .

B: How do you usually make those decisions do you use any tools or do you use your gut feeling or some knowledge?

M: Yes I prefer to use tools and knowledge, because the gut feeling is connected mostly to a higher level decision making, since I am an operative and not a strategist at present. The best way to make a decision is to employ knowledge and the information provided by the tools that I am using to do a certain task given by the management.

B: In what form do you use predictive analytics?

M: We have models which we use and where we put inputs and we manually correct those models so they could give an output that is desirable by our management or that is desirable to be achieved in near future.

B: Sure and even those types of models we can consider them as some form of predictive analytics?

M: Yes, yes but we don't have a system that actually does the calculations for us, actually I am involved in the planning i.e. predictive process and mainly, what I do is just a manual and corrections.

B: Does predictive analytics help you discover new opportunities?

M: Mainly predictive analytics is used to track the behaviour of the customers that are already in our base. Usually those opportunities that you are talking about are given from the side. I think our models are not designed to seek totally new opportunities they just predict the movements of the actual base and the actual activities we have at present in our company.

B: What do you think are the effects on the knowledge at organizational level? Is the knowledge in the organization generated more quickly maybe or is the quality of knowledge increased by the use of those models?

M: By all means, because there was a situation when our company was going through changes and we took on fixed program services, and new models were to be created in our company so we can employ them in order to predict their behaviour. And of course we quickly learned a lot about how those subscribers are behaving in given circumstances, based on historical data. There were subscribers that came due to merger process, there was a lack of information regarding the parameters we needed to work with, so we had to create something on our own in order to know how these subscribers are going to affect our business in near future and in five years. We planned for one year, which is budgeting, and five years planning the whole business planning. So the first years of the merger were a bit difficult, but due to the business things and the models we've employed we could work out how this difficulties are going to affect our work in terms of subscribers, revenues, long term policies and etc.

B: How would you evaluate the decisions you've made based on that knowledge?

M: Actually by employing those models I am managing to find the pattern of behaviour of those users and know how are they going to develop in near future and to see whether the traffic and revenues are going to increase or decrease and whether the fixed telephone is going to used or obsolete, whether the internet traffic is going to grow because we are going to the age of internet and online services. Actually I don't make a decision whether the service is going to be used in near future but I could give an input and say this service is going to be obsolete or these service is going to be better, we should focus on certain services, we shouldn't focus on certain services, so I give recommendations rather than decisions.

B: And those recommendations, they prove to be accurate most of the time?

M: Yes, they do. Because the movements are usually in a way that you can easily base the behaviour of customers based on the historical data.

B: What do you think, how does the predictive analytics influence the time required to make a decision?

M: I think that, mainly it shortens the period of decision making most definitely, because as the time goes by we perfect and improve the models that we are working with. We learn so much about our customer base and how it affects the overall result. And I think that the time for budgeting and business planning is shortened really, because historical experiences had taught us and our management that they are quite accurate with minor changes. Those changes are needed for the management to make predictions desirable for the company to achieve its goals. Actually when I do the planning process I make a real scenario, let's say, this is going to happen if we do things the way do them at present, but if we do this, revenues will increase, traffic will increase, subscribers will increase. I usually give those sorts of recommendations.

B: How do you think it affects the time to authorize actions is it reduced or do you think it prolongs?

M: No I don't think it prolongs. Once the decision-making process is complete, the authorization is just a matter of formality. So when we have the decision-making process shortened, more efficient, more accurate, then authorization is in my opinion totally formal, because they trust the data we are providing.

B: And with the use of predictive analytics do you obtain more data now about the customers, is it increasing faster, do you gather more data than you used to in the past?

M: Actually we are working with data that's available at present, and actually we don't get data we get knowledge from the predictive models. We get knowledge, we get something that we create. We have the data, but we actually get knowledge. And I know that, what I am about to expect from that certain type of model is that, if I change few parameters, what I am going to get is different type of model, that is maybe similar but is more sophisticated, more in- lined with the demands of the environment. We are dealing with a huge amount of data and data won't stop growing. That data needs to be controlled and managed at all times, and when new types of data are introduce, we must respond accordingly in our data bases, data warehouses.

B: Does the predictive analytics had any influence on the procedures you have, when it comes to the development of data warehouses, knowledge repositories or expert systems?

M: Yes, I would say so. We had to make some adjustments to the procedures, since the predictive analytics is dependent on data and the way you manage it reflects on the results that you will get and on the time you will get them. So, in order to be more efficient, we needed to update, sort of, our procedures.

B: You mentioned that you noticed patterns and abnormalities in customers behaviour is this frequently?

M: Yes. If you take roaming patterns for example, usually they have very unique seasonality. If you have tariff models which have certain promotions in certain periods. Customers behave differently rather than they would normally behave. This is the case with prepaid segment also.

B: How do you choose the best alternative to decide and give a recommendation to the higher level of management, is it just you analyzing the numbers that you get, or the tools make an automated decision?

M: No, it is not an automated decision making. A person needs to make the choice. And no, it's not just the numbers that I get that are important, but multiple aspects need to be considered. The telecommunications are specific business which requires very large amount of investments and you have to invest a lot and that affects network. Usually when we compare the total revenues and the costs we look at which was by profit, mostly by profit but sometimes we also choose actions that are desirable to maintain more qualitative goals such as market share... I mean those are numbers but they are related to the brand, to the awareness of people, basically profit parts but sometimes we turn to more qualitative measures.

B: With the use of predictive analytics do you need more or less people to make decisions in the company?

M: Usually it depends on the level of decision-making process. I mean for more basic let's say operative or technical decision making, they should be based on the managers' union or the employers' experiences, but on more strategic level I think it is best to have a sort of team of decision makers which will enhance the decision-making process by giving inputs from various areas. Let's say it's an operational decision. The manager or the employee or the head of the department that is responsible for the certain process must have relative and sufficient knowledge to make the decision, but for something more strategic you have to take all the aspects of the company. So I think as the decisions are growing more and more complex proportional number of decision makers should be involved in the process.

B: Do you think that with predictive analytics more people are becoming information sources, more people generate knowledge for the decision-making process?

M: Yes of course. Usually the plan we are making or the budget we are making requires inputs. Maybe I give 75 % of the data but there are certain departments that are required to predict the behaviour or the patterns of certain parameters in our company. So by giving me inputs which are based on their previous knowledge, which are based on their knowledge that is going to be perhaps based on historical data but also based on the environment we live - inputs from the environment, I think that they can generate the portion of knowledge I need to complete my part of the job.

B: How do you think predictive analytics affects the time spent on meetings, their frequency, do you think that there's an influence on that.

M: Yes it has influence on that, but usually I tend to make those meetings shorter, just to give people instructions and see the final papers when they complete them and afterwards if there's a need to discuss those inputs, will just discuss them, but within very short time matter. I think it should shorten the time, because we are not a new company, we have already accumulated certain knowledge it should shorten the time because we already know what to expect and how the things are going to evolve in the future.

B: Do you think that predictive analytics allows lower level management to make decisions that are good for the company?

M: Well it gives them a sort of more clear view of what their purpose in the company is. It gives them the opportunity to take part into the company’s results. The top management sometimes is not capable to make certain decisions, because they are not fully aware of the sales, processes, issues and they just see the picture more generally. But I think that sometimes the middle management it helps them..... You know.... their voice to be heard and to really drive the work process, to have input into the working process and decisions.

B: How do you think it affects the communication between the colleagues within your department and between the colleagues within other departments do you communicate more than previously with the use of these models of predictive analytics?

M: Yes of course. We must continuously communicate, because they have to be informed about the process. They have to know precisely about the period and the impact their figures are going to have into the entire model. We usually exchange data, because all of the parameters in our company are interconnected. I predict the traffic that has certain impact in different departments. If we predict revenues then we must see how the costs are moving. So we do communicate, but usually the communication time is by phone by e-mail. We don't do meetings because they are obsolete it's just a waste of time.

B: So we are slowly reaching the end of this interview, so I'd like to ask you do you see any problems when working with predictive analytics any sort of problems that you would like to mention?

M: Yes. Sometimes the amount of data employed in those models it's vast, it's very big, so we have problem with the big data base sometimes. It is very hard to extract the desired information and therefore to create the desired knowledge. But somehow we manage to do this.

B: Is there anything else you would like to add maybe about predictive analytics and decision making or do you think that we've covered most of the things?

M: I’d like to say that higher management also includes different inputs when making predictions and decide, outside the data we use in our models. They have different connections with the institutions of the society, they have connections with the peers from the industry, because they have... I don't know... contacts with certain representatives of relevant regulatory bodies, so they should provide us with that kind of input. In an indirect manner, maybe contribute more to the process, because sometimes, there are cases when some environmental issues are not included into the processes, because nobody wants to give us input about. It's a rare case, but it happens sometimes and we have to know everything, we ought to know everything in the best so we can make much better prediction.

B: Thank you very much Marija.

Appendix E: Transcript C-Retail

B – Bojan
N – Regional Sales Manager at C-Retail

B: What is your position in the company and what is your role? What do you do in the company?

N: I 'm regional business manager in the company and I am responsible for [redacted] devices, printers and software solutions.

B: What types of decisions are you required make in your line of work?

N: A combination of strategic decisions in terms of what we are going to do... I'll say again through examples, literally now I just returned from Prague on a conference where they told something new and now in practice I make a decision about what will be applicable for our business. External vendors give us more opportunities, but we do not use all of that. We decide what part will be applicable for doing business in Macedonia, what could pass, and then on a daily, weekly, monthly basis I'm making decisions of all types, in the sense of if we will work with them or not, whether we will give a favourable offer or not, up to the daily level - what response should be given to a particular proposal.

B: How do you make those decisions? Do you use mostly data, some tools, make appointments or base them on a feeling maybe?

N: No, it's not the gut feeling , but I rather use the experience I have when making decisions, because I work for 20 years. So it is experience based, considering what I've worked so far, and naturally some important decisions I do not make just by myself, but together with several colleagues, depending on which level the decision needs to be made. The strategic decisions especially, I do not make alone, but they are made by a group of people.

B: Does the use of predictive analytics helps you discover new opportunities?

N: Throughout all my experience and the whole period ever since our company exists, everything that we do, all the data is recorded, analyzed, predictions are made, and based on those results that we obtain and what they show to us – we make decisions. Our decisions are not based on a "gut feeling". So yes, those analyses quickly show us areas where our attention is required and even new areas where we should invest for instance. We also use a lot of information from outside, like for example we will be entering in the market of smart houses. We got information, we analyzed data, we predicted a demand, a gap that we can potentially fill as a company. We also realize that that will be the future, not only for today, tomorrow and for several years. So it is a strategic decision that we made and we are working on it ever since.

B: Does this mean that using predictive analytics, the knowledge that the company has, increases with a growing trend and speed? How does that affect the quality of the knowledge?

N: Yes , absolutely. All those things that we learn from the analytics, from our experience they constantly increase the knowledge that our company has. That is knowledge that we use when we have to decide whether we should go “left or right”, and of course, the quality of it must be good. We also get a lot of data from our vendors, data which we analyze, make predictions that are almost always accurate. The amount of data that we have is increasing all the time and is increasing fast, so we have to react and analyze it fast. I should tell the example where, many years ago we brought in the first digital machines, first merged computers and photocopiers, while previously there were only regular photocopiers. We were the first in Macedonia, perhaps the first in the Balkans, that brought digital equipment, our experts began to deal with digital copiers and today all of them are doing that. You must have the knowledge to make decisions like that.

B: What do you think of the outcomes from those decisions you make based on predictive analytics?

N: We see that in the future, if we decided correctly or not.

B: Sure. And what does the future usually show you? The fact that you rely predictive analytics to support decisions, is it good for the company? Do you make good decisions based on that?

N: Absolutely, being a successful company for over 20 years and being considered as one of the most successful companies in Macedonia, proves us that the models we are successful, the decisions we make are obviously very good and there is no reason for us to change the way we work.

B: What do you think, how does the predictive analytics affect the time you take to make decisions and to authorize actions according to those decisions?

N: Yes, absolutely, above all, the speed of the reaction is important, even though we find the quality of the decision to be more important. The predictive analytics helps us to react faster. The analysis that we’ve done in the past years allows us, when a certain moment comes, immediately to react and make a decision without the need of additional analyses. Since we have the knowledge, we have the experience, we can easily say yes or no, to go or not go with something, the next time a situation repeats we can decide faster. Again I say, these tools help us to speed up the process of analysis, to come up faster with a decision, an informed decision. With authorization, it is the same thing. Once I make a decision, of course, naturally, I authorize all the actions to be done related with that decision. Very rarely we make decisions using sense, we are always looking for arguments. I work in a company where sometimes mistakes are made but more important is, when you make a mistake to say "I thought it was best because of this and that, and I did and it turned out to be a mistake". You can’t say "I did it because I didn’t know what to do and what it will look like", which is even a bigger mistake.

B: Does the use of predictive analytics lead to increase of the volume of data you generate and store?

N: Yes, the data is constantly increasing, but I must say that the quality of the data itself is increased, it’s not just the volume. Increased quality of the data helps us make decisions with increased quality as well, decisions that turn out to be the right ones for our company. As we learn the benefits from predictive analytics, we tend to ask for more data, gather more data and analyze more data. Of course, the data needs to be monitored and managed at all times, and we have special teams that deal with data, building databases, maintaining data warehouses, because we need to adapt to the environment.

B: Since you brought in the management of data warehouses, I’d like to ask you, do you need to adjust the procedures for constructing knowledge repositories and expert systems, to adjust them to suit the needs of predictive analytics?

N: No, not really. I don’t think that we needed to adjust any procedures. The predictive analytics I think only affects the quantity of the data that we need to store and therefore work with our data warehouses or knowledge repositories as you say. But the procedures are not affected.

B: Do you see any other way, to obtain that kind of information to support your decisions, without using predictive analytics?

N: Yes there is. You can hire somebody to do the same thing for you, analyze your data, make precisions etc. Or, sometimes it happens that our vendors, partners made the analysis and they are willing to share the results with us in order to have mutual benefits, so we don’t need to allocate resources.

B: Does the predictive analytics help you identify patterns, let’s say in customers behaviour, so you can react based on that, launch a new product etc?

N: First of all, we must analyze trends, we must identify them, we must follow them in order to make any conclusion or decision about something. Of course, the predictive analytics helps us do that faster with high quality. We can understand customers’ behaviour and needs, see where the competition is headed so based on that we can make moves and respond to happenings in the environment, make the right offers. Also, predictive analytics helps us understand the context, the scope, the environment we are working in. Having that understood, we can see what the problems are, what kind of decisions are needed so we can make them.

B: Does the predictive analytics give you the opportunity to create different scenarios, to measure maybe the outcome of those different scenarios individually, and to analyze them further?

N: Yes, we’ve always done that. The tools, to models that we use to make predictions usually give a several scenarios, so we can see what could happen if things go one or the other way. If we don’t like how those scenarios look like, then we go back in the process, we change the parameters, we make adjustments. Those scenarios are very important for us. We need to “feel” the environment around us to be able to react and make decisions.

B: Out of those scenarios you mention, who do you choose which one to follow, which one to take? Is the selection an automated process?

N: No, it’s not an automated process. Everything must be analyzed and measure. The tools present us some numbers, sort of KPIs for the different scenarios but they don’t make the decisions for us. It is up to us, the management, to evaluate the scenarios and choose the one that we feel it is suitable the most. Sometimes it can happen that the best scenario that the tool is suggesting does not align with our current objectives. Sometimes there are other factors that should be considered, outside factors like politics, economic climate, legislation. Those things no software can consider when making analysis and predictions, so ultimately decisions are up to us.

B: Do you think that with predictive analytics you need more or less people to make decisions?

N: Less people, for sure. You know why, it's because the tools, predictive analytics, they help us build scenarios, scenarios with different outcomes, different predictions. We don't need, let's say, 10 people to come up with 10 different predictions and debate on them. The tools do that in a much simpler way, cover multiple segments in our line of work, so we can see the outcomes and decide based on them. If we didn't use that, we would be needing for more people to actively participate in making decisions.

B: Do you think that with the use of predictive analytics more people generate knowledge and act as sources of information necessary for decisions to be made, or there is no influence?

N: Definitely yes. More people generate information because when they use the tools and models to make a prediction, they analyze that information and they show it to us, managers. So yes, they generate knowledge and we later use it to make decisions, for example for sales of our products or supply management.

B- Do you think that the use of predictive analytics somehow reflects on the duration of the meetings you have to make decisions on, or on the frequency of those meetings?

N: We have minimized those meetings, and it's important to notice that our meetings are not brainstorming. Each of us, participants, has the task to obtain information that we will consider before hand, after which we then sit for a short time to decide what we do. So, when predictive analytics is used, we have the predictions, we have the information on which we rely so we make conclusions fast when needed.

B: Does the predictive analytics help people from lower hierarchical levels to make good decisions, decisions that are driving forward to company?

N: Yes, I totally agree with that. People at every hierarchical level of our company make all the decisions they possibly can, without communicating with the upper hierarchical levels. They make all the decisions based on the information they have at the moment. Even the operatives can make certain decisions without asking for confirmation from their superiors. People have the right and the obligation to make decisions based on the knowledge we have provided to them. And yes, predictive analytics assists the middle and lower management levels to make decisions. In the process they use the knowledge they get from the data, they rely on it for certain decisions and make them without expected confirmation. Of course, there are some strategic decisions that are up to the top management, but still, you get my point.

B: Do you think that the use of predictive analytics affects the communication between the people within a same department? How about the communication between people from different departments?

N: Yes, both the communication within departments and communication cross-departments are absolutely affected. We want to keep our employees informed, familiar with all the data and all the decisions that are being made with which they are concerned. When the time comes for them to do something, to make a decision, they have the experience and information what needs to be done. To do that, of course, they need to communicate and they need to communicate a lot. When they make some predictive modelling, they get some results, they are supposed to share those results with all the parties that are concerned regardless if they are within the same department or cross-departments. Let’s say, for example, when marketing works on a new strategy, they should have results from analysis made by other departments, and that demands for more and more communication.

B: As we slowly reach the end of the interview, I’d like to ask what your general impression of predictive analytics is, can you foresee any future trends?

N: I have always used it, I still use it now, I will continue using it and all my employees and colleagues will continue using it. Ideas don’t fall out of the sky and don’t appear in our dreams. There is just a pool of data and it’s up to us to extract information out of it.

B: Do you notice any problems related to the use of predictive analytics in your company?

N: Some would say these sort of analytics is a huge cost for our company. But I wouldn’t say it is something which is so easy to quantify and measure. However, the cost of making decisions which are bad for the company is far greater.

B: Lastly, do you feel like we missed something in our talk? Would you like to add something else?

N: I think that should be all. All in all, to make any kind of decision, you really must have as much information as possible. When you have bad information, the decision will always be bad. If you don’t have the information, it will still be a bad decision and there is no excuse for that. Using my gut, I can only fill in a lotto ticket, should the numbers appear in my dreams. That is certainly not the way any modern company should operate.

B: Thank you very much for your time.

Appendix F: Transcript IKEA

F – Fadi
M – Visual Merchandise Leader at IKEA Sweden

F: Hello and thank you for accepting this interview and the valuable information that you provide based on your own experience. First I want to ask you about your position in the company and you role in the company?

M: For now I work as a merchandiser, so I'm responsible for all the sales in here. But one year ago I was site leader in the lightning department and I have planned a lot of source like a site specialist so yeah, I have done a lot of things.

F: Interesting position. I would like to ask you what type of decisions are you required to make - for example in your current position in the sales department and in your previous position?

M: For now, I firstly see how this decision is going to look like, the first comes with why and then we come with how, how we are going to solve this problem.

F: You are providing, building sales campaign on the website with certain purposes?

M: If we have a problem with the sale, and the salesman comes to me and says we have a problem we must solve it... I say: “Ok we're going to solve it this way”.

F: How do you make those decisions? Based on a tool, or on a computer system, or maybe on previous experience?

M: Previous experience, like, the role I'm in now, we don't use that much tools, but when you work at website as a site leader you only work with tools all the time because then you need to have all of the site history and all defect procedures because they have a lot of installed logic here in IKEA, so we have a lot of key figures who go after.

F: What type of tools do you use in the sales department?

M: We have a sales program that has to put every sales figure in (how much it sells?) and then we have all of these parameter cards, how long it takes for us to get articles, and how much we must have in stock so we wouldn't get out of stock and everything. It's imperative to work with all the figures on daily basis so we would never run out of stock and also to have all of these logistic parameters right.

F: Now we are going to talk about decision making on daily basis what types of tools do you use to make decisions and do these tools help you to discover new opportunities and new options?

Not in that way. The answer is how to manage the department or to run the business in the cheapest way possible... and sometimes is counter - productive, because I want to sell this more or I don't want to sell this article, but also depends on how big are the effects on the one coming home, where to place it in the store.

F: You mean about the logic?

M: Yeah the logistic figures are all put in the system and then the system tells us how much we should have all the time in the store. If we don't have it in the shop, then we will have it in the storage. And if we have it in the storage then it's not available for the customers then the article is costing a lot of money.

F: So at the sales you have two objectives. The first one is selling the product and the second is managing the logistics and stocking them in a warehouse, right?

M: Yes, and sometimes you can feel that the program and all of these logistics key figures are interconnected and tied between, because we can't do work as we want, and sometimes we can't order the articles that we want, because of the ordering time and because we don't have a self sustainable ordering system that can allow to call someone tomorrow... you need to prepare for six weeks before, for the system.

F: Does predictive analytics help you gain organizational knowledge, experience that's provided within the team or the organization?

M: Yes it does help, because we get all these figures from these tools so we can see all the sales history, all suggestions. It doesn't matter which year it is, if it's the global economical curve, it can be very low or high, because it is following in the same period every year. The top depends on how much money people have or spent, but the curve is following the same trend during one year. Last year the curve reached very high level within a few days, so we wanted to sell more and therefore I've made a forecast for the week.

F: Does predictive analytics help you to produce knowledge faster?

M: Yes. Once a year they make a forecast what they are going to sell the following year, so the service office can know the probable amount and quantity of production.

F: Year after year you collect this knowledge with the help of this tool but the quality of the knowledge is it enhanced and increased?

M: Yes of course. And it tells us also.... because otherwise we will always forget that autumn is coming and it is getting darker, and people use to buy more candle light... then we must go afterwards and higher up our forecasts. So if we use the tools in a right way we can achieve increased sale of candle lights in May, or September, October.

F: Are the tools Interactive? Can they provide evaluation of the values - for example, this value should be higher?

M: So you can already know if you pre-order, you can put in the figures for the autumn for candle lights, and when it's autumn and darkness is coming you are already prepared and that is really good. It is a quick pick and the best one.

F: You are making decision based on predictive analytics and after that how do you evaluate the outcome of this decision? Have you made the right decision and made it faster than usually? How do you evaluate that?

M: I don't think that they evaluate.... they don't evaluate this. We are having enough talk all the time and the salesman is the one that makes the sale, it's not the tool that makes the sales it is more salesman care. And if we have too much stock at home, it costs money then the tool will alert us that something is wrong. So every week you get alert and alarm from the tool. This article you must look at it carefully,. Why don't you sell them? You have too much stock. So it's a daily work and it's fun.

F: How do you think that these tools affect the time required to make decisions? Is it faster or slower to make a decision?

M: I think that it's much easier to work in long terms now, if you have planned your following year of sales but it takes more time on daily basis because you need to work with putting the input information in order to get and look in the alerts and alarms, so the tool is always refreshed, because, if you don't put in the correct figures you don't get the right results. So it takes more time. Before ten years ago when this program wasn't published on the market and everyone was working with pen and paper, also memory and experience it took maybe longer time to learn, but the input information was much quicker, because they had another ordering system.

F: So it was quicker working with paper?

M: Yeah because the time of ordering some commodity was assisted through call, and after ordering, it was delivered the next day.

F: So if you think it was quicker with paper, why do you switched in this type of system?

M: It is quicker for us to solve the problems on daily basis, but the time needed for reaching the customers is longer. Now we have more... what can I say... stocks in the warehouse all the time we don't have out of stock articles except for minority cases of calls. Because of human progress we have to have 9000 articles a year, you can't even remember them all. So this too is helpful for selling more and having everything in stock all the time.

F: When making decisions do you wait for supervisors' or higher decisions' authorization? When decision time it's short do you think that this tool will help with reduction of time to authorize actions?

M: Yeah I think it's both. You feel like it takes time, because now you must sit, fill in and put in the figures into the tool. Before you used to remember and fix a little bit of here and there, but with the tool you really need to sit for a couple of hours and put it in. And we feel like it's taking time for us. So I think it's wider but it gets more out of it.

F: Do you think that you obtain more data with the use of predictive analytics, more information? How do you find the quality of that information?

M: This data that we get is a really good data but also it's not very different from the data that we don't work with. It is because if you look in some figures, and for example we don't sell much of this article, maybe it will be enough to halt for five days, because the problem may be with the delivery. If you don't know that then you'll think "Oh the transit is going down" - lower than the forecast. So it is a combination of analysis and the experience that you have as a site leader. You have to know your articles and your shop on your own fingers, because these are the key figures in the system.

F: Most of the data that you provide for the figures are they growing for the most of the commodities and items?

M: Yes it's in the beginning increasing rate, but when you work and learn in the right way, it's not coming wrong, and if you put in the right figures you don't get much alerted and alarmed and then you have to keep it like that.

F: Is there another way to get those figures and data?

M: Yes they have another system like Excel, so we can use and make an excel list then you can make a search and make your own time and take the figures that you want. We have so much figures that we use.

F: Do you think that using of this tool is affecting the way of storing the knowledge in files or data bases?

M: Hmm... I don't know really....

F: Do you think it's changing over time? For example the data and knowledge storing system?

M: No. This system that we have now it's quite new, so it is changing all the time. But it is getting data from our old system. This new system we have it for about a year it is quite new. So we are learning and new things are emerging all the time and it is getting better and better.

F: Do you think its functions are modifiable upon your request and demands?

M: Yes, yes. They have this service, and if there's something that it's not strong or wise we send them some wishes, for example why and what shouldn't be there, it should be here and I want to know this for the system I want to know that. Afterwards they will put this into their program and tools build in the changes and update them.

F: Does this tool is helping in detection of patterns or abnormalities of customers or sales behaviour?

M: Yes, it was the date... I don't remember now, for how many weeks exact... but you can see the whole history there.

F: Can the tool predict patterns and after a week or so you can say this prediction was wrong or not? Will it improve over time (the prediction)?

M: Yes we always get average week from the system, and the average rate is based on 3 weeks and on 10 weeks. So we can always see within a shorter period... No I think it's two weeks for the shorter time, and then the average rate within 10 weeks. Then you can see the trend if it is going up or down firstly for the two week predictions.

F: Is it correct?

M: Yes. It is correct when using the right figures. But like I said before you must know your shop because on contrary you can be out of stock for a 6 days. In that case the average rate is low compared to what it should be if you had enough stock for two weeks.

F: Do you have categorization for the customers or for the products?

M: We have categorization for the products, knowing which product we should always have in stock. So we have 4 categorizations for the articles 1,2,3,4. Number 4 it can be out of stock here and then.

F: How do you categorize the products? Do you use data provided by predictive analytics or not?

M: Yes predictive analytics also shows how important the articles are. And if it is for example a book case which is a key run, we should never really be out of stock with this one. So if we have a little tea spoon out of stock, that's fine, that's not so important. And that's why categorization is for. Because if we run out of tea spoons for two weeks we have some other commodities the customers can buy. But if we run out of stock commodities that are important... no, no, no.

F: Do you think that when making decisions you have to have some options and alternatives and can the tool provide this options and alternatives?

M: Yes... because if you take for an example we have an area in the store, and ok from the interior we must sell something, and we going to have this. Then you can see it in the tools the forecast for the delivery office when is it going to be out of stock, for example in two weeks. So if it is going out of stock in two weeks of course we don't take this product, because it's a lot of work for us to build something up for one week when it is soon out of stock, and then we put out something else. So yes, you can see.

F: Does this tool help you to evaluate the outcome and select the best option, we put this in this empty place and it predicts somehow how it would sale?

M: Yes the tool reacts immediately. If you put something and it starts selling more then it also can alert for the products, articles because if you don't have high forecast for the product, like for example it is situated back in the corner and that's not suitable for the customer then we immediately put the product on the main isle - as a result , of course the sales will grow up from 10% to 200% and if we don't put in the forecast for what is going to sell more the system will tell us "Hello you have put something, you sell like crazy" - before you've made 5 sales a week and now you are making 50 pieces a week - "Hello hello, you must do something".

F: When speaking about alternatives, and choosing between them, does the tool make the selection or you have to make the choice on your own?

M: The tool is giving me information. If I want to sell a product I represent it to the tool and if it say that it would be almost out of stock, if I choose June or July, there is no point for me to highlight this product and try to sell more, because we are not going to have this product in stock here in Sweden or maybe in Europe, and therefore I must choose another article. So the tool is giving me information then I decide.

F: So you don't have a part of this tool to make decisions instead of you?

M: No it gives only information and helps to run the business.

F: How do you put the human factor in the process of making decision with the help of this tool?

M: You need to care for it right and put in the right figures all the time. So if the human behind it put in the wrong figures, it will not keep it running correctly, then like I said garbage in – garbage out. Then we are out of stock with some articles or we have to much in stock of some articles and very little in stock of other articles...

F: Speaking about choosing alternatives and finally picking decisions, do you think that it depends more on human experience?

M: Yes it is the human experience that is making the decisions. It is not the tool. The tool is just giving us information so we can go for the decisions that we make. If the tool says no, there's nowhere stock for this or it will take ten weeks before you get this article then we must make another decision so it will send the information.

F: Ok. Now we are going to talk about the use of predictive analytics. How do you think it affects the people making decisions? Do you think that more or less people are generating knowledge i.e. providing information in order to take decisions?

M: I think we try to get more people, to have the knowledge and to understand the information that you get from the tool, because it is too much information, so we try to teach and train as many co-workers as we can so they can understand what to read as information.

F: Do you think there are more people providing useable information in order to undertake decisions with the use of predictive analytics or no, on contrary, with the use of this tool less people provide information?

M: I don't think that many co-workers are making decisions like that. Because of the tool, if you get the information why is coming out of stock or why it's coming home. Because they don't take decisions what they should place there instead or something exact. It is the sales leader or the shop keeper that are doing that. So it is a very good information tool for them.

F: Okay. And speaking of other departments and other units. Do you think that people only provide information without undertaking decisions, and do you think that more people are providing information with the use of this tool or any other predictive analytics tool?

M: They don't take decisions from this tool, because the tool is only helping us and it's not leading us to take decisions. It is so, for the running business, for the long term priorities...

F: Let's say that you are going to take a decision about the sale, but you need information from multiple sources and the people will provide "the sales are going up from the last week, we have only this number of items in the warehouse" ... I don't know maybe the market department will say " We need to help more and more next week" so you provide some information from many sources and then you take a decision. So this is what I mean, people are providing information. So do you think more people are providing information based on those tools?

M: The people like the sales leader for Sweden in different departments, they don't have this kind of tool like we have in the store. They have other tools, maybe they have something same but for whole Sweden.

F: Not like reading all the time?

M: No. So they can say "ok now we are going to sell this number of pieces of test product that we had last week", and then they have the other people who are working with defining process and logistics come in to make alert and alarm that is going to be out of stock maybe this product, or that we are having for example two weeks, let's say for whole Sweden less in stock , then the site is sending alert and alarm "ok don't push this product, because you can't get neither one for about 3 weeks. So don't push it.

F: To make a decision, do you think there are more people required in order to come up with a decision, for example a big or specific decision?

M: No.

F: And using such tools like predictive analytics do you think that people from different departments are now enabled to make decisions more evenly?

M: Yes, but it depends. We can take more decision when we are having a campaign, we have a kitchen campaign now, I think. Then we can go to the tool and see the history of the last year campaign how much did we sold from this article, then we will already know at present which product we are going to take home. So we must say which one is going to make the highest order from these products and so on. So like I've said the tool is giving us information, afterwards we decide what we are going to do with this information. Therefore you need the training, the sell training, to know how to read information. It is the system that's causing the need of analytic person, but if you don't know the trends of customers' behaviour and how the shop is working then you miss to put in a lot of figures in the computer and that results with a lack of information after couple of weeks.

F: I want to speak now about the meetings. Do you think that meetings depend on some information provided by tools like predictive analytics? Do you think that those meetings now take more time or less time using that information?

M: I think it is the same, because now we ought to have a different kind of meetings. Now we already have these different figures and information from the tool and it's much easier and we tend to have a lot of discussion around this then we had before, when we didn't had this figures. Maybe that's more because we are going through more details that are provided with the right figures and we can discuss other things, maybe planning how to do this campaign and so on.

F: Now I would like to speak about the hierarchy i.e. the levels in IKEA. Do you think that such tools enable people from different levels to make more correspondent and accurate decisions?

M: Yes. I think that with this tool that we have for the sale, the co-workers from the floor, they would take the decisions. Not the management team and the source. They don't take any decisions from this tool, because they don't work with it. It's the co-workers and the sales leader who work with it.

F: After those sales person or sales leaders take the decisions, how do you evaluate those decisions or how do they evaluate the decisions? Like for example "Ok we have made the right decision".

M: It is the same. It's the sales figure and also key figures for the logistics that is telling. Because it doesn't matter for how much you sell for. If it sells for 1 million but it costs 950.000 to sell it you have you own earn 50.000, and if it sells for 1 million and costs 500.000 sell it. So it's a really nice balancer. You make a sell but you lower the cost. Because you can't have the sale when the cost is running upwards also, because then you will be running out of money.

F: Once you have a decision does it need approval from the higher level or they just take decision and authorize it?

M: It's of course like, they can't reveal up the whole department, because I want my department to look efficient and therefore there's a lot of planning of resources and so on. During the daily business you have to change some articles and products and if it's up on top of another article, which product are you going to put there instead, it's a co-workers’ shield from the department.

F: But speaking about those little decisions that need more approval how many levels do they need to pass in order to be approved for performing a certain action?

M: You need to go to the sales manager here in the store and present to him why do you want to do this what are the benefits and then they take it in a management group and decide ok they can do this or not. Because, of course, every shop keeper will tell someone on depot "ah I would always want reveal the nicest things and have the newest deportments" but they can't reveal the whole store all the time, so they need to make decisions with more and the most rush to do something. It is too much outgoing and so on.

F: But do they base data on such tools or no?

M: No. Most of the time when we do the big reveal, it is because we have a lot of new products and articles that are coming in. So we need to do that big reveal. But then we take data out of these tools. So we have all the figures and we know how to build the new department. So we take them in revision in order we don't put the wrong product on wrong place, so we can have the right product on the right place. It is what the tool is telling us where to put a certain product.

F: Let's speak about the communication between the staff in same departments or same unit and maybe other departments. Using these tools, do you think that staff is required to communicate more?

M: Yes, maybe. If something is going wrong.... with the tool ... no the tool can't go wrong it's because what are you putting in it. Not typically. Only when something goes wrong, but otherwise no. There is a logistics meeting, that is once a week, when we put in all the key figures for the logistic. Each department is assembling them and so on. For example the cost and the handling of the products does not cost too much money or does not going up.

F: Is it for the same department or different departments?

M: It's for all departments together. One representative for each department, and then they get through all the key figures, which department must to work with it and what do you need to work with the following week.

F: So we are about to finish now.

M: Yeah?

F: What do you have as a general impression from predictive analytics tool, in term of accepting or decision making?

M: It's giving information on how it has been for trends for member one products or one area for example candles or lightning. Because the lightning department is really up and down like now is going for light the sunlight 24 hours. They don't buy much lamp settle. But when you go to darkness it increases the sale. And if you look in the tool, it gives you information how the sale is working, when is ups and downs. So you can make a decision how to run the business and any goal. Even if we plan for a new store: "Ok we going to open it in May. Maybe we don't need this much talk and this high forecast in the lightning department”. But in May everybody is going to be out in the sun and everything and all the summer furniture, then we need to have a really high forecast in this department, but in lightning really low forecast. So, based on history, then we will decide what we are going to have in the future.

F: Thinking about predictive analytics tools, what in your opinion, the related problems are with such tool and the first problems that you can think about?

M: I don't see any problems. Sometimes it is not giving you... they have not built the system with the information as you wanted. Different departments need different information, because it's also, a lot of things behind.

F: Like it's not customizable or?

M: No. But then you need to work with this tool where you can do your and compare list of analyzes from figures.

F: So it's like time consuming?

M: Yes. But it is only one time, if you have done one list and you use updates then you get the figures out once a week. But then you also need to know Excel to know how to work with it. If you don't know it, it’s going to be harder but if you don't know it you don't know the things for measuring so therefore you don't suffer. But maybe you have to work little harder with other things, because you need to search information by yourself and it's a little longer.

F: What do you like to add in the aspect of this domain or maybe something that we've missed in this interview?

M: I think... because I've been working here for so long and also I worked in other store before IKEA. It's that, that every time we work we the sale we have new programs and everything is going to take so much time and so many paper. But the last I never do, I simply, the average time that you are working with the system and also all the paperwork that we have it's almost the same like before, but in a different way.

F: So is it time consuming compared with the old fashion way?

M: Yes... I think the time consuming it's almost the same, but we are more efficient in other areas. So we are spending time for that, because the system helps to keep the same level all the time so we don't need to run and look like this, but the work with meters and parameters and everything, I think is the same time spent. But in this situation the system is keeping all the data for us, and we don't have to do by ourselves any more. So it's much easier to search and find them.

F: Ok good. So that's it?

M: That's it.

F: Ok thank you for having this interview.

Appendix G: Transcript Semos

B – Bojan
D – Mr Daniel Joskovski

B: Thank you for this interview today. I'd like you to ask you first, what is your position at the company, what do you do, what is your role here at Semos?

D: I work as IT consultant focusing on Microsoft technologies, and in the last few years, my focus is on predictive analytics and modelling. So my role is to do things like leading implementation and development of IT solutions and also make trainings for the clients, the users of the systems

B: What kind of decisions do the people that are using the escort server for instance, what kind of decisions do they make, do they analyze data or they work with the data or are they mainly technical support people?

D: They are technical and business persons. They usually explain to other data analyzers or somebody else in the company or what they can achieve with the platform and generally they don't make other type of decisions except of these that I've mentioned. These people assist the ones that make decisions in the companies.

B: Do you think that predictive analytics help these users to discover new opportunities?

D: Yes definitely. They usually work with predictive analytics to get better understanding of the market, of their customers, to see what products to launch and so. Because there are different kinds, there are plenty of algorithms and there are also open software libraries for predictive analytics , so this libraries are now included, you can work with machine learning in Azure Cloud in Microsoft, so you can do almost everything - what is known in science right now. So definitely it is very useful for someone who wants to use this prediction.

B: And for the organizations and companies who use this kind of tools how do you think it's influencing the knowledge within the organization, the knowledge about the environment about the customers? Do you think that the knowledge is generated faster and the quality of the knowledge is improved?

D: It generates more qualitative and quantitative knowledge. Actually it's fast process by nature it is highly optimized and takes everything into account, so it's, by my opinion, 70% better than decisions that are made by some old fashioned managers.

B: And do you think that the decisions that are made based on predictive analytics are better, so to say?

D: Yes they are better if they are configured in a right way and used for the right purpose. You now that you should use the right tool for the right problem. So if you make a mistake by choosing different tool for different problem the result will be bad. But if the technical person knows enough how to explain to data analyst, not need to be achieved, the result will be good. Otherwise you know: garbage in – garbage out.

B: And what do you think how does the use of predictive analytics affects the time to make decisions and authorize actions for them?

D: Time is shortened extremely. When you talk about business intelligence we think about analyzes which are done non-stop in real time. So if it lasts more than five seconds basically it's better. So it should be fast and basically it needs to be presented to the management, so if these conditions are reached it will be ok and the time will be very short for making decisions. But that all depends on how this system is built, depends on the design of the system. There are poor systems and sophisticated rich systems who have everything you need, there are systems that have many things that you don't need to observe, but basically if everything is ok the results will be good.

B: Do you think that companies who use predictive analytics are generating more data with the use of predictive analytics or you think that's not connected?

D: No it is connected. For example, cases for predictive are the ads on websites on Facebook, there are all based on some classifications, algorithms who process you favourite food, fun and everything. It’s the same for our clients. They analyze something like their market, customer’s actions, trends, make predictions and generate information. So basically it has an influence on the volume of data and the ways how you are going to deal with it, store it, manage it, access it and so on. Our clients are usually required to make some changes in their procedures for working with and managing data.

B: The information that the users get with the use of predictive analytics, do you think there's other way to get that same information or do you see predictive analytics as a unique resource?

D: I see predictive analytics as a unique resource for generating new knowledge. Even human mind works on the exact same system basically. Consider the neural networks and all the other algorithms that exist, related with making any type of prediction.

B: Do you think that users identify patterns of customers' behaviour and they prove those patterns to be valid let’s say by making sales or decisions on that?

D: Yes this is also one of the scenarios like fraud detection which are use for all this situations. Because you know, people are used to discover patterns in everything. For example if I turn two times around and then starts two rain I will think that it started to rain because of my turning.. You know Murphy’s Law, if you wash your car it will rain. That is in human nature and you will say: Ok I'll wash my car to predict rain. Yes, I know that is too simple and predictive analytics doesn’t work like that, but I wanted to show you that identifying patterns is very important and companies want to do that in every way possible. The predictive analytics is there to help them.

B: Do you think that when using predictive analytics the users get different types of scenarios, analyze those scenarios? Do they compare the probable outcomes of those scenarios and then choose based on that?

D: Yes. that is how data mining actually works. So we use for example 70% of the data for training the system and then 30 % of data for scoring, for testing the system. Then we have for example average or mean error. In that way we can also evaluate the strength or the accuracy of the algorithms we use and we can see if it's good or bad in predictions and so on. So with time and experience and with good design we can achieve a reduction of errors.

B: How do decision makers make the choice of the right scenario? Does the system do it for them, or is it the human factor only that has influence?

D: Managers should rely on predictive analytics. It gives them the perfect way to see the environment where they work. But when you say making a choice, or making a decision, the final call of course is on the decision makers’ side. The ball is in their court. Meaning, the system cannot tell them you should 100% go with this scenario because this is the best way for your business. There are other factors they consider like economical trends, politics, regulation, where the competition is and so, and not everything can be actually predicted. Managers cannot get the perfect formula for success from a single system.

B: Do you think that the companies that are using predictive analytics are required less or more people to make decisions?

D: Oh basically less people are required. When the system is in place, maybe more are needed during the building of the system because the system does not go with optimized value you should use also under-ways for making decisions. By the time the system is tested and evaluated there is a need for less people. The system will provide them with all the input the decision makers need so they don’t need to ask for input from people from many departments like sales, marketing and so on.

B: Do you think that more people act as information source, as somebody who will generate knowledge for decisions making, with the use of these systems?

D: Yes, because if you don't have the system you don't make decisions by throwing the dice so you must collect information and process it manually. So basically the process is the same but it takes too much time. With the system, more people in the organization are able to work and process data which later decision makers can use. You can't make decisions without collecting information and analyze it. Without analyzes you cannot predict anything. It's important only how this analyzes would be done. Algorithms are the same basically. There aren't something new.

B: Do you think that meetings are more frequent or less frequent? Also about the time spent on meetings, do you think they last more or less considering predictive analytics is used?

D: Meetings are the same. At the moment when I have data, it doesn't matter how data is produced by human or by some system, on meeting people make decisions that are based on facts, predictions or analyzes. So the meetings number and time spent will stay the same basically. Maybe will last shorter if we use some predictive analytics system. But basically same number of meetings and processes of decision making will be there.

B: Do you think that with predictive analytics people from lower hierarchical level in the company can make good decisions with a satisfactory level of quality?

D: That depends on hierarchy and on what kind of decisions they are making. For example, in 2009, I worked on some system for banking which allow clerk to approve loan request up to 10.000 euro for example. But if the request is more than 10.000 euro then someone else should make the decision about that loan. But based on all metrics I will allow somebody from a lower hierarchy to use predictive analytics but only to some level of budget or something else. We are not always deciding about money there are other things also like insurance, life insurance or property insurance etc.

B: The management of the clerk, are they happy how the system performs and how the clerk performs with decision making?

D: With these systems we always exclude subjective factors. So if everything is inputted in the system, the system says ok the risk is 70%, and I have a rule if the risk is less than 20 % you can approve it. Clerk can argue to check if he can approve it. But the main factor in decision making will be again the system of predictive analytics.

B: Do you think that with predictive analytics people are required to communicate more among them and with people from different departments to come up with decision or you think that it doesn't affect the communication within departments?

D: Well it affects the communication but the communication of this type can be automatic. So if I can't decide I can ask, for example 3 managers and they will receive the call from me with all the data and they have buttons “approve” or “disapprove”. Everything can be communicated in less than 30 seconds and then the decision can be made. But if you do it the old fashion way it will take days for the decision to be made. The system does most of the work and you don’t have to ask other people to do things that you need in order to do something else.

B: And the same would apply probably for communication between different departments with different hierarchical levels?

D: Yes, definitely.

B: So we are slowly reaching the end of this talk and I'd like you to ask what is your general impression of the use of predictive analytics in terms of decision making? How do you see it?

D: I see it as a future and unavoidable future. So that is the reason why I am focused on predictive analytics. So I think this is something that will worth more and more in the future.

B: Do you think that every type of company should incorporate it or they need to be in certain level of development?

D: No not every company, but everything. So that means for example rooters can employ predictive analytics for choosing the right root from one note to another road note for better communication. So on every level not only on a level of making decision in a company. Everybody even in tracking, maybe cars should decide where to go when talking about cars without a driver Google cars. The possibilities are unlimited. On one of my presentations I have a person who has been customer in Israel he had employed such system for prediction of where a certain hard disk will fail and then they replace the hard disk just one hour before it fails. Right on time. Yes. So in that way the system is never endangered to fail due to a failure of hard drive. That is why I am very involved now in predictive analytics. Actually this is different level of using of computer power. So it's not like nowadays programming, but generating new knowledge.

B: And do you see any problems associated with the use of predictive analytics happening now or upcoming maybe in the future?

D: Yes, like always, you can't predict everything. So if I could predict everything, I would be billionaire till now. So I can't predict for example stock rates or who will win the lotto so people should use this as decision supportive system, nothing else.

B: Ok is there something else that you would like to add about predictive analytics and decision making or do you think that we've covered most of the aspects here?

D: I don't know maybe I want to point to go for example to go to Microsoft website and check machine learning with Azure. It's well documented you can try it for free for 30 days and see what is that.

B: Perfect thank you very much!

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