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Data to Insight

A Sense Making Perspective in Business Intelligence and Analytics

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Abstract

Motivation and Objective

This study investigates how analysts generate from data using business intelligence tools. The motivation for study at the premise that organizations are finding it very challenging to generate insights from a vast amount of structured, semi-structured and unstructured data. The initial problem background indicate that this may be because organizations are silo driven, have data governance issues, data quality issues, BI analyst lack skills as well as data literacy competence that is needed to analyse and interpret data to understand customers, and among other issues, which limits the use of business intelligence and analytics to generate insights (Deloitte, 2017; Harvard Business Review, 2012; American Marketing Association, 2017).

Hence, the process of generating insights is a very slow process, and organizations want better adoption and understanding to increase progress in daily operations/production and other areas so that they may use their capabilities to the best of their extent, as well as generate real business value (Deloitte, 2017; Harvard Business Review, 2012; American Marketing Association, 2017). For this research, two case sites are selected for the study: IKEA AB, Sweden and CDON AB, Sweden. For these two case sites, the study further investigates two specific domains: BI Innovation at IKEA and Business Controlling at CDON.

Method of data gathering and analysis

The motivation is to understand the BI analysts' sensemaking perspective when generating insights from data, the qualitative case study research method is adopted as a more appropriate method. Accordingly, the unit of analysis are BI analysts at their respective domains, and semi-structured interviews were conducted to collect research data. The findings are presented individually for each case site, for which a cross case analysis have been conducted using a matrix table to bring forth a unified understanding of insight generation from data.

Overview of findings

The study finds several key activities that act as the generators of insight in regard to how data is evaluated. Insight-generating actions and characteristics by the BI-analysts include: having clear business questions, Just-In-Time models, access to integrated databases using modern technology, business domain understanding, understanding of data quality and plausibility, understanding of data governance issues, application and sharing of solutions (dashboards, reports etc.) through a community approach, as well as having skills in BI tools, maths, statistics and programming. Granted these requirements for insight generation are fulfilled, insight generation from data will be less time-consuming, in that way the process of insight generation will become faster. The end goals of organizations are to generate overall business value and the adoption of BI&A will become more achievable.

Implications

- Data governance in terms of control mechanism needs to be put into place for organizations to avoid legal and financial complications, which is a subject that needs further research. In addition, it affects the over data quality.
- Expert BI-skills and experience needs to be shared among other BI analysts and business personnel to close the knowledge gap in organizations. This is also a subject area that calls for further research.
- Data quality through good-bookkeeping, data governance and the use of advanced BI-tools can insure and impact reproducibility and reusability. This is another area that would benefit from being a focus by organizations and may likewise benefit from further elaboration in future research.
- The experimental approach towards BI&A can possibly be improved by organizations by them supporting such practices. Also, further research is needed in this area as well.
- The understanding of business knowledge, pure logics, and clear business models can be improved by organization from within through training programs and other methods in the BI&A domain. This area also needs further research.
- We have made our contribution to the scientific knowledge area of BI&A, which needed further explanation in terms of how to generate insight from data.

1 Background Introduction

The value of data is reflected universally and recognized as the new oil (Brownlow et al, 2015). This is because commercial and non-commercial organizations are taking the opportunity to capitalize on the value of data to remain competitive in the market (Brownlow et al, 2015; Sorescu, 2017). According to recent studies, business firms that are data driven are on average 5-6 percent more productive and profitable than their competitors in the market (McAfee and Brynjolfsson, 2012; Hayashi, 2014, Brownlow et al, 2015). In contrast, firms that fail to implement data driven practices lose a great deal of competitive advantage, resulting in lost revenues and risks survival in the market (Brownlow et al, 2015).

For data driven organizations, the data has become a vital tool in the creation of value for business. It provides comprehensive view of market conditions, customer needs and preferences, potential risks, and allows organization to align products and services with changing market patterns (EY, 2015). The top 10 drivers for an organization to implement analytics of large quantities of data are, according to a survey of 270 senior executives by EY (2015), to: (1) help them to better understand customers, (2) improve products and services, (3) improve the data management of existing data, (4) create new revenue streams, (5) be seen as necessity for new business models, (6) monetize on existing data, (7) build leaner and improved internal efficiencies, (8) find and exploit new data sources, (9) facilitate better management of governance, risk and compliance, and (10) improve the detection and prevention of fraud.

Yet, to become a data driven organization, firms need business intelligence and analytics (BI&A) to leverage opportunities that can arise from data (Chen et al, 2012). That means firms are moving from sourcing/producing data to consumption of data (Fisher, 2009). Another research survey conducted among 2252 IT executives worldwide placed BI&A as number one in their shopping list (Luftman et al, 2015). Most recent studies have also forecasted the growth in BI&A sector to reach $22.8 billion by the end of 2020 (Kihn et al, 2017).

However, if we reflect on the past, the evolution BI&A started back in around 1970s and 1980s with the key characteristics of having database management systems (DBMS-based), structured content, dashboard and scorecards, as well as data mining (Chen et al., 2012; Olszak, 2016). The BI&A trend of turning data to consumption didn't stop, but further developed with time around the 1990s to 2005, when web based structured content, web analytics/intelligence and social media analytics enabled organizations to present information and also interact with customers directly using online internet (Olszak, 2016). Moreover, with the passage of time, the expansion of BI&A was further developed in web analytics, so organization now also can process and analyse unstructured data produced through Web 2.0 in large quantities (Chen at al., 2012; Olszak, 2016).

With this increasing development happening in BI&A, the competitive market forces and overall industry have started to demand organizations to go beyond relying on internal available sources of structured data, because capabilities of acquiring the data have also expanded gradually with time, and have enabled organizations to get data from various sources of structured and unstructured data available in different forms, for example sensors producing data

which are connected via the Internet of Things (IoT), social media (Twitter etc), web free content, images and video files among many others (Chen et al, 2012; Olszak, 2016).

The large amount of available data has allowed organizations the opportunity to capitalize and create value out of data, for example in location-aware analysis, person centred analysis, context-relevant analysis and or mobile visualization, etc (Chen et al, 2012; Olszak, 2016). With these types of analyses and many others, organizations have proactively leveraged and also used data in real-time by integrating it with business processes, operations (available to staff), and stretched it enough to improve the firm's information delivery and decision support functionality (Olszak, 2016).

Now, organizations view this as a shift from tactical data delivery that uses data modelling, aggregation and clustering, to using BI&A tools by turning and reducing the volume, veracity, and volatility of data to small number of relevant cues, for example alerts, key performance indicators, metrics and patterns, and more (Namvar et al, 2018). These cues, alerts and patterns are then to be used strategically to filter and extract value from data and convert it to a meaningful insight, which should then support business decision making in areas such as operations, finance or marketing as well as other important business areas (Namvar, 2018; KPMG, 2015).

1.1 Problem Statement

The first problem, data circulating the internet is more than a zettabyte (KPMG, 2015). And of which 95% of data is unstructured (Gandomi and Haider, 2015). The large volume of amount of data as discussed earlier, not only provides opportunities, but also poses challenges for firms so they may prepare and develop capabilities accordingly in insight generation from a broad range of structured, semi-structured and unstructured data from various sources (KPMG, 2015; Kandel et al., 2012). And on top of that large volume structured and unstructured data comes with variety of problems and threats, such as silos keeping departmental data which is limiting access, data governance issues (sensitivity, legal or financial), data quality issues, data sourcing issues, lack of skills and data literacy competence needed to analyse data, critically manipulation and management of data, interpretation of data to understand customers or businesses, as well as the fact that some have non-experimental approaches towards data and prefer less risk it (Deloitte, 2017; Harvard Business Review, 2012; American Marketing Association, 2017).

This is over all seen as a time consuming and very slow process that impacts insight generation from data and organizations want more and better adoption of **sense** making to increase progress and enhance the insight generation from data, so that they may use their capabilities to their best abilities and generate business value out of it (Deloitte, 2017; Harvard Business Review, 2012; American Marketing Association, 2017). However, this also means organizations to rely on data analyst to generate insight so that they may model customer interaction, optimize operations, improve production, inform sales, allow innovation, competition, improve productivity and to implement business decision making (Kandel et al., 2012; Chen et al, 2012; Lycett et al, 2013; Sharma et al, 2014).

The second part of the problem is that very little scientific research is being conducted in insight generation from data within the BI&A domain (Chen et al, 2012; Lycett et al, 2013; Sharma et al, 2014). Therefore, a research study that can facilitate better comprehension of BI&A in contemporary business environments, which would help organizations to facilitate well informed and on-time business decisions, is needed (Namvar et al., 2018).

Given the importance of BI&A in academia and the practical world and of the role of data analyst's generating insight from data, this research will aim to investigate how data analyst make sense out of data to generate insights using business intelligence tools. Therefore, by asking the research question in the manner of "How", the study can explain and seek to provide answers about the causal mechanisms that are at work regarding a phenomenon (Recker, 2013, p.29). In addition, a research question seeking the "How" is more appropriate to understand people's perception and meaning (Yin, 2014; Silverman, 2013). Therefore, the research study will seek to answer and bring understanding as to:

How do analysts generate insights from data using business intelligence tools?

Additionally, for this study, a case study research method has been selected, since it is more appropriate for research questions relating to answering "How" (Yin, 2014; Recker, 2013). Also, for the same reason, a qualitative research design is appropriate because of the strength of this type of research is that we can capture natural occurring data in depth within its context (Silverman, 2013; Recker, 2013).

Furthermore, for this study we have used the Data/Frame theory of sensemaking, mainly by Klein et al (2007), to investigate and explain our research findings. The reason is that generating insight is an iterative process, done by foraging information and mapping attributes from data to set hypotheses, and accordingly evaluate those to comprehend the subsequent multi-faceted relationships therein (Russell et al, 1993; Jolaoso et al, 2015). This means that insight generation is an outcome/product of sensemaking while conducting data analysis (Russell et al, 1993; Jolaoso et al, 2015).

The data frame theory of sensemaking has also proven to be relevant and beneficial in many other research studies, such as the analytical process of detecting and identifying anomalous behaviour in maritime traffic data and where vast amount of data from multiple sources is very common (Riveiro et al, 2009) and in a study conducted partially with the intention to understand mobile visual analytics (Anna et al, 2010). It is a relevant framework that has been used in different contexts, since the goal of sense making is to generate insights. Additionally, upon further investigation, we also found out that there was no research study that has used data-frame-theory as a theoretical frame in BI&A context. Hence, we believe that it is very relevant and can contribute to academic and industry knowledge in BI&A context and in literature of data-frame-theory as well. Thus, the Data/Frame-theory framework of sensemaking will allow this study to attempt to bring understanding to how insights are generated from data using BI&A tools.

1.2 Purpose

The purpose of the study is to bring an understanding of how insight is generated from vast amounts of data using BI&A tools by the BI analyst. The case sites are the two organizations IKEA AB and CDON AB in Sweden, and unit of analysis are the participants in this research working as BI analyst in their respective domains: BI-Innovation in IKEA and Business Controlling in CDON.

The method used in this research is qualitative in nature and a case study methodology is selected for us to better understand the phenomena by investigating insight generation from data in a BI&A context, in order bring to surface context dependent knowledge (Andersen and Kragh, 2010). The purpose was also to apply cross case analysis to understand in a unified manner, how analysts generate insight from data using BI&A tools (Yin, 2014). The intention of cross case analysis was not however to point out which case site is better than other, but rather to bring a wider understanding of insight generation from data.

Also, the theory used in the study, the Data/Frame theory of sensemaking by Klein et al. (2007) has never been used in the BI&A context in similar organizations before. Additionally, by using the Data/Frame-theory of sensemaking along with a case study research method as mentioned earlier, the study contributes to informing the industry of the understanding of generating insight from data and contributes to the scientific research in BI&A in allowing researchers and practitioners alike to understand data-frame-theory in a BI&A context.

1.3 Delimitation

This thesis is delimited towards the study of the BI-innovation domain in the first case, in addition to Business Controlling within the BI&A domain in the second case, to find out how organizational insight is derived from sensemaking in both contexts. Furthermore, this thesis is not examining organizational culture as an aspect, neither social subtleties that can have significant effects in and of themselves on BI&A adoption (Rimvydas et al, 2016). The nature of this thesis means we are deriving our findings considering sensemaking theory in a BI&A context (Klein et al, 2007), thus omitting any performance related metrics, software or hardware specifications of BI&A systems, as well as any thorough examination of the systems in and of themselves (Endo et al, 2016). Rather, BI&A tools/systems are a potential enabler for insight generation.

1.4 Limitations

While it is always possible to interview more people when there is little to no time constraints, we had to stay within the time frame that was given, thus proving time to be a limitation. While the sampling is limited however, the data gathered comes from highly experienced BI&A analysts with an average of over 10 years of experience in their field. While the findings may not be generalizable to a larger population, they do fit within the context of organizational BI&A and can thus be studied as such.

2 Theoretical Framework

The theoretical framework defines business intelligence and sensemaking before presenting in-depth literature of the Data/Frame theory of sensemaking by Klein et al (2007). As mentioned earlier in the background, the goal of sensemaking is to generate insight and not the other way around. Hence sensemaking should not be confused with it being the opposite to insight, instead insight is an outcome of the sensemaking process (Russell et al, 1993; Jolaoso et al., 2015).

2.1 Defining Business Intelligence and Analytics

While the term Business Intelligence was not conceived until the early 1990's by Gartner Group analyst Howard Dresner, the exact use of Business Intelligence and Analytics (BI&A for short) has evolved throughout history (Watson and Wixom, 2007), from early versions of decision support systems in the 1970's, to online analytical processing, predictive analysis, executive information and other types of decision support applications. In 2007, BI&A projects were the top technology priority, recognized by business leaders and CIOs as a critical instrument in providing innovation and effectiveness (Watson and Wixom, 2007). Today, BI&A seen as a process, illustratable by frameworks, that deals with getting data in, and getting data out.

Getting data in is referred to as warehousing, which involves sorting data from systems from which it is sourced, which usually are differentiated technical platforms and structures of data, into data stores, also known as warehouses (Watson and Wixom, 2007; Chen et al, 2012). The data can be sourced from either the organization itself, a business partner, or an external provider. Because of the inherent complexity of the process regarding data migration, the data worked up to become usable for decision-making for example, adding extra identifiers within the datasets to facilitate more aspects and derivations from said datasets (Watson and Wixom, 2007). This is where metadata plays a role, since it deals with the understanding of these complexities and the manipulation of the various characteristics that the data may have. It describes the nature of data itself, such as values, sizes, data owners and so forth, and is used for transparency purposes as data migrates from source, to warehouse, to end user. The data that is refined and transformed is then placed into data stores (Watson and Wixom, 2007; Chaudhuri et al, 2011).

The most time consuming and hardest aspect of BI&A is the process of acquiring the data, which is why this process generates over 50% of unforeseen project costs. In addition, it needs 80% of the effort and time to accomplish (Watson and Wixom, 2007). The causes for this can be linked to inadequate quality in the data, older technology, as well as politics regarding who owns the data (Watson and Wixom, 2007).

The main value of BI&A however, comes from making beneficial decisions from the data (Watson and Wixom, 2007). This is where business users can do online analytical processing, predictive analyses and reporting. This is also why the process of getting data out is the more

attention-grabbing aspect of BI&A from an organizational perspective. This also what is usually meant when organizations speak of BI&A (Watson and Wixom, 2007; Elbashir et al, 2008).

Additionally, as pointed out by Watson and Wixom (2007), when BI&A - business alignment takes place, the business strategy can be greatly enhanced using BI&A in terms of organizational transformation and new business models. This however needs to be followed by a belief in BI&A by the senior management, as it needs to be driven from the top layer for it to be of any use. Adequate resources and the want for information-based decision-making is needed for this to work out (Watson and Wixom, 2007). It is also likewise important to consider the sector in which BI&A takes place, as the relationship between business process performance and organizational performance varies (Elbashir et al, 2008). This makes it necessary to take a good look at the context when measuring BI&A powered IT systems.

2.2 Defining Sense Making

Sensemaking as an information task is meant to create an understanding of a concept, knowledge area, situation, problem or work task, to inform actions (Zhang and Soergel, 2014). The actions may include learning about new domains, solving ill structured issues, obtaining situational awareness, and exchanging knowledge with others (Pontis and Blandford, 2016; Pirolli and Russell, 2011) Therefore, sensemaking is seen as a prerequisite to problem solving, decision making, planning or executing a plan (Zhang and Soergel, 2014).

In broader terms, sensemaking be a cognitive process practiced by people or organizations within their natural settings (Weick, 1995; Klein et al, 2007). The main theme around sensemaking entails that, when a person or organization experiences deficiency in the ability to understand, grasp or unable to grip the current events, this is when sensemaking comes into play to respond to new and excepted events or sudden situations (Weick, 1995; Klein et al, 2007). The new or excepted events are of people's' beliefs, distrust of messages and other possible data (Klein et al, 2007). This means that sensemaking allows people to embed and currently know what supposition or hypothesis to link with the observation with inference, to describe and examine, and to assist actions or activities before routines can emerge from performing tasks or to improve existing tasks (Pirolli and Card, 2005; Klein et al, 2007).

Sensemaking activities allows business executives (people) to comprehend, understand and realize the events or problems triggered by unexpected revelations that makes them doubt their prior understanding and thus will require from them to constantly monitor issues faced by their respective department (Klein et al, 2007; Klein et al, 2006b). Sensemaking as activities are not only triggered by the detection of anomalies but are used to extend one's understanding of what is going on (Klein et al, 2007; Yi et al, 2008). Sensemaking goes beyond the comprehension of stimuli. For example, in problem detection, sensemaking is to determine if the regularities are worth investigating more closely. It is also about making new findings and discoveries or to map relationships to see the current state of location by connecting the dots/relationships, as well as to diagnose and explain how things work by forming explanations, predicting potential problems in order to prevent those with the help of anticipatory thinking, projecting future states - which is similar to anticipatory thinking in order to prepare beforehand and finally, problem identification - to identify or verify variables in a particular event or situation (Thomas et al, 1993; Klein et al, 2007).

Sensemaking characteristics as described are vast and have been investigated by many researchers over the years (Dervin 1983; Weick, 1995; Schraagen et al, 2008). However, the most common aspects in sensemaking is the requirement of mental activities and skills (Jolaoso et al., 2015; Namvar et al, 2018). These mental activities and skills can be explained as characteristics using a holistic definition for sensemaking, such as,

"Sensemaking is a process of clarifying and removing ambiguity and uncertainty by searching for and organizing similarities and differences from data sources through which goal-directed interpretations for decision-making are established. Therefore, sensemaking as a process is the foundation of knowledge creation, Where the quality of sensemaking affects the quality of knowledge produced and the outcome of decisions predicated on that knowledge" (Namvar et al, 2018 cited in Weick et al, 2008; Russell et al, 1993; Brown et al, 2008; Dervin, 1998).

A good example of sensemaking would be the tasks that often relate with the reconstruction of events, for example, how steps and action occur in processes and other variety of tasks related to sensemaking (Pontis and Blandford, 2016), such as the understanding of features, costs, service plans and trade-offs in consumer decision making, while buying a product or by collecting, organizing, and grasping information about a certain medical condition and its treatment options (Pontis and Blandford, 2016; Bhavnani, 2002; Bhavnani et al, 2003; Pirolli and Card, 2005). Moreover, sensemaking characteristics are well summarized by Klein et al (2007) in the Data/Frame Theory of sensemaking, which is further discussed, and we found some forms-of-sensemaking to be interesting and relevant in the context our research thesis which will be outlined next.

2.3 Forms of Sense Making

There are seven types of sensemaking as given in Figure 1, The top oval is mapping data and frame and the ovals below it are, elaborating a frame, questioning a frame, preserving a frame, comparing frames, reframing, and constructing or finding a frame (Klein et al, 2010). The frame operates in different ways, because the activity of maintaining/retaining a frame is different from the construction of a new frame (Klein et al, 2010; Pontis and Blandford, 2016). Some important frame operating attributes and aspects mentioned by Klein et al, (2010) are given below and followed by in depth literature discussion on each seven types of sensemaking.

The starting point of sensemaking can be different depending on the requirement or trigger, for example the trigger initiated from data needing further elaboration or change in a frame. Some instances the frame itself will require a search for data and the definition for what counts for data.

- An anomaly can also trigger sensemaking.
- People may choose between competing and plausible frames.
- The order of activities varies, sometimes people construct frames before even questioning it.
- People may simply recognize frames and do not come down to any construct.
- People may alter data to fit the frame, or they may alter the frame.

The forms of sensemaking also have important traits such as the role of experts having richer repertoire, sensemaking supporting functional understanding that allows just-in-time mental models and form dynamics. These are traits and roles are explored below.

2.3.1 Experts having richer repertoire

While experts are dealing with information pertaining to the operations, specialist can perform at higher level than that of beginners, although both the expert and beginner could adopt the same logical and abductive inferencing in the same way and can show no difference in the reasoning process (Klein et al, 2007). In addition, experts and beginner information specialists use inferring methods, such as cause and effect relationships when exposed to information data operational work, though experts are more proficient in doing this because they can hold the benefit of previous knowledge and richer mental models than beginners, as they might have limited previous work-related knowledge (Pontis and Blandford, 2016; Klein et al, 2007).

The experts in particular have better and richer mental models, such as greater variety, finer differentiation and broader understanding of phenomena with in-depth and more plausible awareness of context and are also insightful because experts use previous knowledge frames as routines to achieve more ways of accomplishing things and can widen their range of frames that they can draw upon (Klein et al, 2007). This also allows experts to dig deeper into selected data points (Pontis and Blandford, 2016). Additionally, experts are aware of distinctions, related knowledge, and have better understand of the functions they would like to accomplish in a task, hence existing functional understanding helps in exploration (Klein et al, 2007).

2.3.2 Sensemaking to Achieve Functional Understanding

Experts tend to prefer a functional understanding at the same time of having abstract understanding, and this is because they would like to know what to do when they face situations or tasks since they prefer a more practical approach towards their tasks (Klein et al, 2007). However, an abstract understanding could also help experts in understanding what is going on (Klein et al, 2007). Hence, Sense making involves the development of what is possible and what is not; it is about how competence can be expanded to achieve the purpose using wider repertoires of frames to find potential candidates (Klein et al, 2007).

Furthermore, functional understanding can also be achieved through initiating action that helps people to reduce uncertainty and vagueness (Klein et al, 2007). In that way, people act to think, which helps in shaping their interpretation (Klein et al, 2007).

2.3.3 Just-in-time Mental Models

Klein et al (2007) distinguishes between comprehensive and just-in-time mental models. The former captures essential relationships, what people mostly deal with are partial knowledge and casual relationships, meaning there are gaps in the understandings. A just-in-time mental model consists of going beyond limited knowledge in which there lays a gap, to get a notion of the current situation. This means that a just-in-time mental model is one that is constructed at a time of need, rather than being dependent on a time aspect. Klein et al (2007) further suggests that people should primarily rely in just-in-time mental models as opposed to complete

and elaborate mental models that describe and deal with an entire system. When inferring relationships and correspondence between two constructs, this inference can become an anchor granted it provides sufficient relevance to the task and can therefore lead to a chain of inferences. Despite not having an elaborated mental model, one is still able to perform in an effective manner Klein et al (2007).

Moreover, sensemaking can take different and alternative ways with information operations specialists and in other domains, hence there is no fixed structure or process of sense making. Also, the other types of sense making cannot be ignored; otherwise our understanding of sense making can become too general to be useful (Klein et al, 2007). Therefore, forms of sensemaking illustrate the different ways of sensemaking, which will be discussed in detail below.

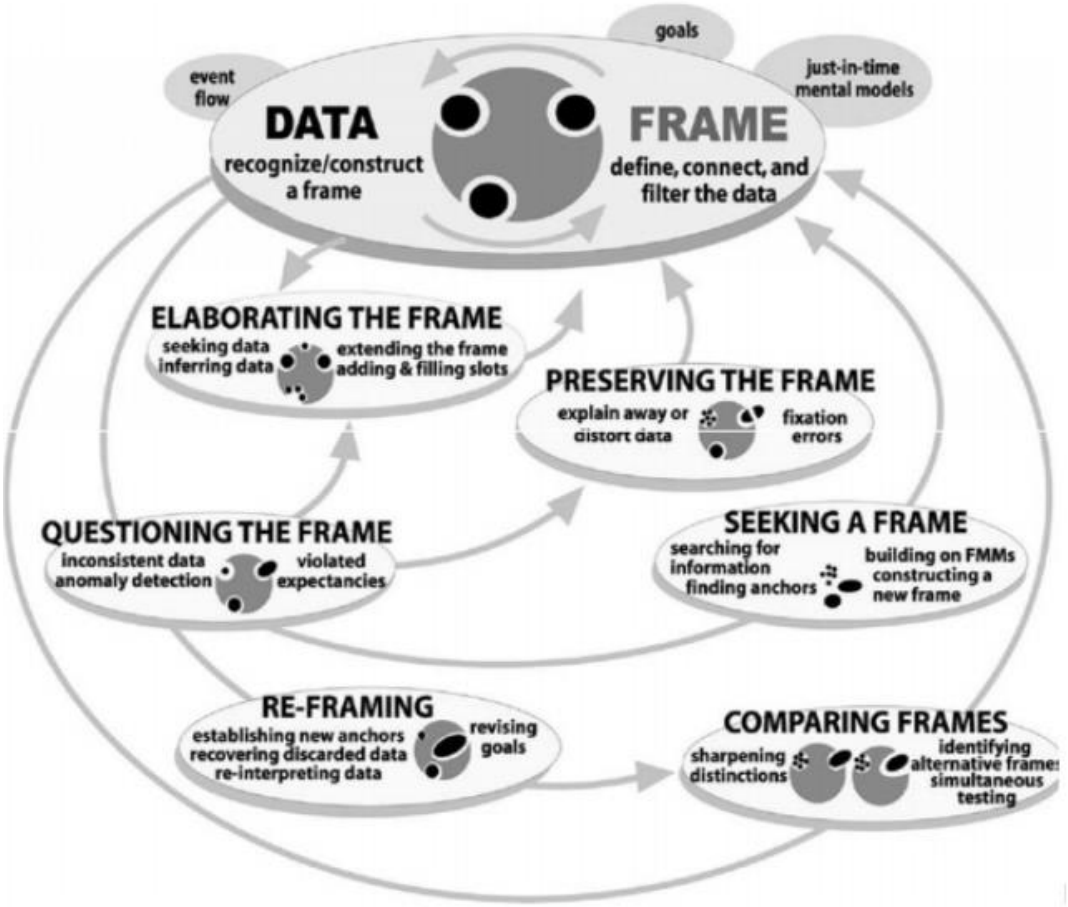


Figure 1 Data Frame Theory of SenseMaking (Klein et al, 2007)

The top oval in Figure 1 is an ongoing basic cycle of frame and data when new events happen, and people take actions while trying to make sense of the events. Here, the process is an ongoing one to achieve goals and objectives, attend to event or create just-in-time models (Klein et al, 2007).

2.4 Connecting Data and a Frame

Connecting data and frame is a conscious process that depends on the available data and information; for example, for an individual's aim or objective, the collection of frames and their motivations are important, otherwise, there is no need for it (Pontis and Blandford, 2016). The motivation of person towards the task may be interrupted by the workload, tiredness level and commitment towards the activity or situation (Klein et al, 2007). However, the characteristics of a frame used by persons are based on the collected data, personal motivations or repertoire of personal frames (Klein et al, 2007). And to define a frame, it is a sense making process and is seen as a deliberate activity, where reasoning is employed using a conscious activity that can also be influenced by unconscious processes, such as, automatic recognition of how to frame a set of events based on pattern matching and recognition that in some instances will not require a conscious process (Pontis and Blandford, 2016; Klein et al, 2007). Collected material such as transcripts, photographs and video clips all constitute parts that together can help to make up a frame (Kolko, 2010). This can also limit the construction of a frame, as variables such as software limitations and lack of storage space can all play a part in and of themselves that can limit the ability of the collector of the information to fully grasp the concept (Kolko, 2010).

Moreover, the process of sense making requires fitting data into a frame or fitting a frame around the data (Klein et al, 2007). The emphasis here is to understand the interplay between data and frames as two entities (Klein et al, 2007). Data representing the interpreted signs of events and frames are the explanatory frames of the account for the data (Klein et al, 2007). One can react to data elements by constructing frame, such as, a story, script, map, or other types of structures but at the same time the collection of frames may affect the decision about what data to consider and how will they will interpret the data (Klein et al, 2007; Pontis and Blandford, 2016).

Although data and frame are two entities, they must be balanced in situations (surprises) when people think the data does not fit into the frames. Sense making will be initiated to change or completely replace the frame with more relevant ones, and the opposite reaction would be to utilize the existing frame and find new data or modify existing data to find better frames (Klein et al, 2007). Sense making is about expansion of signs by searching for frames within where signs will fit together and will make sense, and this be a regular cycle between data and frames as explanations (Weick, 1995; Klein et al, 2007).

2.5 Elaborating the Frame

When elaborating and extending the frames, people will not seek to replace these until new surprises or anomalies emerge (Klein et al, 2007; Pontis and Blandford, 2016). More details about the frame will be added to fill the empty slots by extending and finding the relevant explanations (Klein et al, 2007; Pontis and Blandford, 2016). Additionally, it is also possible that there will exist more than one explanation of the task frame depending on its nature (Pontis and Blandford, 2016). This means that the process of sensemaking continues, if there are unexplained key data elements or key components of a frame (Klein, et al, 2007). Should more perceived benefits for more exploration arise, the process of sensemaking by expanding the frame may continue by seeking and inferring data (Klein et al, 2007; Pontis and Blandford, 2016). The process continues until their meaning of the data is somewhat tangible and

cohesive (Kolko, 2010). The motivation behind sense making thus decreases with time once the relevant data is taken into consideration (Klein et al, 2007) and as a frame seems relatively specified and valid, and the content can be freely moved and manipulated (Kolko, 2010).

People may define a search strategy or adopt completely new strategy when looking for new sources of information; for example, an empirical study conducted by Pontis and Blandford (2016) used forms of sensing making and identified that people filled slots using the previous frame, but data anchors used in the previous frames that may not be relevant can pose conceptual strain. However, when they were able to find new and relevant information, that allowed them to gain better understanding of the situation, and they may consider the data anchor as a candidate influencer. However, information data elements are not the perfect representation of reality but are framed (constructed), since we cannot remember all the events that took place, as individuals perceive and remember things differently depending on our goals and experiences (Klein et al, 2007 cited in Medin et al, 1997 and Wisniewski et al, 1994).

2.6 Questioning the Frame

The questioning of the frame is activated when surprises arise and inconsistencies of data with frames under consideration do not support it anymore (Klein et al, 2007; Pontis and Blandford, 2016). People may need to replace the frame or adjust details in the frame on which they have initially relied (Klein et al, 2007).

The frame maybe is incorrect because the change in circumstances changed, or data is inconsistent and inaccurate (Klein et al, 2007). This means that data might not correspond to the frame, because frame(s) allow people to have expectations and when expectations fail, so does the quality of the frame, which makes it questionable by the people (Klein et al, 2007). People's emotional reactions can also play role in sense making, for example feeling of uncertainty or distress caused by the loss of confidence in a frame (Klein et al, 2007).

Also, when questioning the frame, people may either ask themselves questions based on the newly found influential factors, such as, 'is the source of information correct?'. If not, then the quality of the data can be gauged (Pontis and Blandford, 2016). Additionally, people rely on their background knowledge to asses if to support the influential information data indicator (Pontis and Blandford, 2016).

So, when frames are questioned because of inconsistent data, anomaly detection or violated expectancies, either the frame will be re-framed by establishing new anchors, recovering discarded data, re-interpreting data and revising goals, or people might seek a frame by searching for information finding anchors, constructing new frames, or completely abolish the frame by preserving the frame to explain away the distorted data (Klein et al, 2007; Pontis and Blandford, 2016). Some of these areas are further explored in the literature review below.

2.7 Reframing

The idea of reframing is not only to accumulate inconsistent or contrary evidences but also to replace frame(s) in order make ways for searching and defining cues, and for cues to recommend a replacement frame, both, cues and framing working simultaneously (Klein et al, 2007;

Pontis and Blandford, 2016). Kolko (2010) mentions that reframing is about the process of attempting to recast a current frame to a new perspective. This is possible by viewing the current frame or situation from the perspective of, for example, someone with a different role, level or other kind of background. The current point of interest is thus seen in a new way, unearthing new links that may have been hidden before, or taking shifting the attention from the center of focus (Kolko, 2010).

As mentioned by Klein et al (2007, cited in Duncker, 1945), reframing or reformulating is important in order to gain insight into solutions to a certain problem and how it is understood. In one example, now classic 'radiation problem', where the frame was pertaining to 'How to use radiation to destroy a tumour without damaging the healthy tissue surrounding the tumour?' The problem stated in this way made it difficult for subjects to find solutions (Klein et al, 2007). Nevertheless, if the subjects reframed the problem from, 'how to use radiation to treat a tumour without destroying healthy tissue' to 'how to minimize the intensity of the radiation except at the site of the tumour' (Klein et al, 2007, p.141). In this way the reframing helps people to consider data elements that they have previously rejected, and now the cues fit, hence sense making is seen as retrospective understanding (Klein et al, 2007). Moreover, reframing may also involve comparing multiple frames as when the requirement arises. This area in literature is further discussed below.

2.8 Comparing Multiple Frames

Sometime multiple frames will be needed to judge what is really going on (Klein et al, 2007; Pontis and Blandford, 2016). Studies indicate that people are tracking up to three frames at the same time; for example, it is mentioned by Klein et al (2007, citing in Feltovich et al, 1984) that when experts broke free of preserved frames in their research on pediatric cardiologists, they were able to identify up to three alternative frames. This is being a deliberate execution to sharpen their understanding, for example, in the study of clustering diseases that shared similar symptoms. They were hence able to make a fine-grained diagnosis (Klein et al, 2007). The given strategy can be referred to as 'logical competitor set' (LCS) as a way of identifying critical details (Klein et al, 2007 cited in Feltovich et al, 1984). Logical competitor set serves as an interconnected memory unit, representing a category build of multiple frames when one member of the set will activate the complete set of for example, similar cardiac conditions that need to be contrasted (Klein et al, 2007).

However, depending on the task, the decision maker tested all available competing members of the set simultaneously or may choose to test most related member (Klein et al, 2007). Additionally, if the data element is used as an anchor in one frame, it might not be possible to use it in another or competing frame (Klein et al, 2007). Kolko (2010) sees this step as forging the connections to examine the relationship between the points of interest. One must logically asses these connections, which then produces knowledge as new and existing elements are combined (Kolko, 2010).

2.9 Seeking a Frame

People tend to find frames when exposed to data that might just not even make any sense, or when the existing frame is in question and they may replace a frame with another (Klein et al, 2007). This process may also include looking for analogies, searching for more data to find anchors for constructing new frames (Klein et al, 2010).

The nature and the combination of sense making activities differ based on the demands of the given task and the available expertise of the sense maker (Klein et al, 2007). Sense making activities have different barriers to overcome, hence they must be treated differently. The Figure 1 illustrates the different activities; for example, support offered to a person in sense making can be different, such when a person might be offered data elements that were taken away before, and now becomes applicable compared to the support given to person who has become disoriented and only needs one or two anchors (data) to derive a new frame. The process of seeking a frame can also be pattern recognition, as one way of finding frames by looking at data comes through the perception of differences, similarities, possibilities and patterns (Crossan et al, 1999).

2.9.1 Frame Inferencing from Key Anchors

As surprises becomes a reality, key data elements can in some cases serve as anchors that enables the creation of an understanding. These anchors are tied to the original frame, which is then used in the search for further elements of data (Klein et al, 2007). What this means is that frames are constructed by the conclusion that follows the key anchors. According to Klein et al (2007, cited in Klein and Crandall, 1995), frames are assembled from a selection of causal factors and are then examined for the soundness of the collection, after which they may imagine how things would have turned out in terms of causation or how they would have played out.

2.10 Preserving the Frame

A frame is usually preserved when the data do not match the frame (Klein et al, 2007). This means that the inconsistent data functions as indicators of the explanation as defective, hence preserved (Klein et al, 2007). The preservation is conducted because it is considered a mistake to discard the data that may also help to describe how reutilization of divergence is sustained (Klein et al, 2007). An example of this is given by Klein et al (2007, citing in Feltovich et al, 2001) is of knowledge shields, used by cardiologists to preserve a frame in the face of countervailing evidence. The preservation of frames by cardiologists was to minimize the importance of a contrasting data, for example arguing from authority based on the preserved frame, resorting to bad analogies, avoiding secondary consequences or effects or arguing from special cases or asserting that a principle has a restricted applicability (Klein et al, 2007). However, the preservation of frame is not necessarily important when there are no uses for it; just because person merely preserves a frame, he/she needs to do it, but rather than the criteria of preserving, the frame is deemed important (Klein et al, 2007). The criteria of fixing a frame as mentioned by Klein et al (2007, citing in De Keyser and Woods, 1993) is of the frame preservation error in nuclear power plant industry, and their account of frame error was that the initial understanding was incorrect, hence the decision maker kept this incorrect explanation in the face of future opportunities that might have arisen (Klein et al, 2007).

In another example, the preservation of frame could have been avoided and discarded; for example, the process of preserving an inaccurate frame, such as, inaccurate preservation of the land navigation, where error creates further errors when journey points and landmarks are incorrectly identified, and the person bends the map (Klein et al, 2007). People might get lost if they attach higher dependence on an inaccurate anchor and then trying to interpret other data elements to fit the inaccuracy, which will lead to tampering the sense making process (Klein et al, 2010). So, the frame preservation is used as directing attention, which is one of the functions of frame (Klein et al, 2010).

3 Research Methodology

3.1 Research strategy

A qualitative research strategy is chosen to answer the research question, ***how do analyst generate insights from data using business intelligence tools?*** The method chosen is motivated by the intricate and highly contextual nature of the study, a thorough insight was imperative to understand and examine the patterns embedded in analyst perception and meaning while interpreting and generating insights from data. A qualitative paradigm is best suited to explain perspectives and meaning by analysing them considering literature, the Data/Frame Theory of sensemaking within a BI&A context (Bhattacherjee, 2012; Klein, 2007; Gummesson, 2003; Orlikowski and Baroudi, 1991).

Having said that, the scientific approaches and discoveries of Information Systems and Sense making within the context of this study are therefore based on the subjective and personal experiences of the interviewees. Hence, the explanatory way of approach lends itself well to this kind of research since we are examining a context-based topic (Recker, 2013; Bhattacherjee, 2012).

Selection Criteria of Two Domains within Two Case Studies, IKEA and CDON

The aim of selecting two different domains at two cases sited is not to investigate which organization is better, but rather to take an opportunistic approach and gain better understanding of the problem phenomena. However, each case site and its contribution and relevance to BI&A context is discussed in each case context in the following discussion.

Furthermore, in this research interviews are conducted at two large Swedish business firms, IKEA AB and CDON AB. This approach is taken to avoid single-case study bias (Easton, 2013), as two case studies are more robust, and we as researchers can gain better understanding of phenomena under investigation, compared to single-case study (Recker, 2013; Yin, 2014). After the collection of data from semi-structured interviews, data is carefully transcribed, and answers are grouped together for each case site separately. In addition, after completing the transcription process, software tool Nvivo is used by conducting open coding, after which axial coding was employed to make higher-level categories, followed by selective coding for both cases separately (Bhattacherjee, 2012).

The findings and analysis for both studies are presented individually and analysed, and then s cross case synthesis is conducted by matching patterns using a word-table to point out the similarities and differences (Yin, 2014). In addition, once all the findings and analysis are presented, the discussion is presented followed by recommendations and conclusions in the end. Additionally, some details have been taken care of while approaching the case sites, which allowed the study to utilize the four strengths as outlined by Recker (2013):

- Phenomena have been studied in their natural setting.

- Complexities that may arise are understood considering interviews, since they can provide extra knowledge of experiences and practices that have been noted and understood by us as researchers, elevating the meanings and intricacies from the collected data.
- New insights have been highlighted to allow explanation approach towards emerging topics.
- Moreover, data to insight generation is contextual and specific to the people and context that are being interviewed (Klein et al, 2010). Hence, employing a case study research with an explanatory approach lends itself well to the topic of this thesis, since questions pertaining to "how" have been researched (Bhattacherjee, 2012; Recker, 2013). Our goal has been to understand insight generation through sensemaking in a BI&A-context and suggest implications thereof.

3.2 Case Context

3.2.1 IKEA AB, Sweden

IKEA is the world's largest retailer in furniture, founded by Ingvar Kamprad in 1943 with a humble cash reward given by his father for getting good grades (IKEA, 2018c; Business, Insider, 2016). They have stores in over 20 countries worldwide, all of which are operated under franchise agreements, which the exception of one IKEA store in the Netherlands (IKEA, 2018a; IKEA, 2018c). The concept of IKEA is about providing affordable furniture for affordable prices, while still maintaining and combining function, design, quality and value, all while being sustainable. Part of the process is to pack their products in a way that facilitates saving space, saving money, and being environmentally aware. The customer building the furniture him- or herself (IKEA, 2018a) also facilitates this. In 2017, IKEA's total revenue grew by 1,7% percent, amounting to 36, 3 billion euros. Retail sales was 34.1 billion euros (IKEA, 2018b).

IKEA is a big user of data in their logistics/supply chain, marketing, distribution, marketing and innovation design (IKEA, 2018a). It is a big organization and data analysis is used in many domains for decision-making (IKEA, 2018b).

3.2.1.1 IKEA Case Relevance to Research Area

For this study, we have selected BI-Innovation department within IKEA, Sweden to investigate how data analysts generate insights from data using BI&A tools. The BI analysts work with business intelligence and analytics innovation, helping other departments locally and globally to produce better reports and analyses of data that helps them to increase their customer engagement. IKEA collects data from various internal sources as well as external; the main purpose is to derive new understanding in their area of customer engagement by understanding their needs and wants of everyday life.

The case of IKEA and domain business intelligence and innovation lends itself very well, since the case domain holds BI&A technologies (Qlikview, IBM Cognos and others), people work with big data and conduct various data analysis, and it is a suitable case site in terms of context. In this way the research study is able to produce richer and in-depth insight and understanding of the phenomena related to the research question that is studied and answered

using real-life natural-setting (Recker, 2013). Additionally, the case research method best suited and useful for real-life settings (Bhattacherjee, 2012).

3.2.2 CDON AB, Sweden

CDON was launched in 1999 and sets itself up as a pioneer in Nordic e-commerce (Qliro Group, 2018). Initially the company started selling media products and later got into offering various products mainly driven by 1500 external merchants selling goods at CDON from 2013 and onwards.

CDON is an ecommerce marketplace in Nordic countries offering broad range of consumer electronics, mobile phones, books, games, films, sports and leisure good, clothing, furnishing and toys (Qliro Group, 2018). The CDON brand is well known among 1.8 million Nordic customers, and prides itself for the success in wide range of goods/services and lower prices with a focus on Sweden, Norway, Denmark and Finland (Qliro Group, 2018), where online consumers can purchase various products and take advantage of competitive prices offered with easy payments and efficient deliveries (Qliro Group, 2018).

The business model of CDON, since its inception in 1999, is supported by two pillars: first, selling their own products from their own inventory procured from well-known brands and suppliers to be sold to consumers using their e-commerce platform, and secondly, the external merchants that pay a commission based on the sales through CDON (Qliro Group, 2018).

In addition, CDON consumers prefer and appreciate the option to buy multiple items and compare prices at the same time, this approach benefits merchants from the traffic and services generated by the marketplace (Qliro Group, 2018).

In the future, the CDON Marketplace will continue to evolve its transformation (Qliro Group, 2018). The focus is also on bringing onboard the e-merchants that have strong market coverage in their respective categories (Qliro Group, 2018).

3.2.2.1 CDON Case Relevance to Research Area

The CDON case and the BI&A domain within the company working with data analysis for business controlling is selected because in this way, the research study will produce richer and in-depth insight about the phenomena occurring in natural setting (Recker, 2013).

Also, the case involves the three important aspects, such as information technology as BI&A tools (QlikView), people as data analysts that use BI&A tools, the context domain, which is business control department at CDON, all of which makes this an ideal and relevant case study. Questions regarding where in-depth and richer insight come about and how data analyst generate insight from data using BI&A tools can be explained and answered for this research thesis.

3.3 Unit of Analysis

The study aims at investigating two individual case sites (IKEA and CDON) and their respective domains: BI-innovation department at IKEA and CDON business controlling department working with data analysis. At these respective departments, BI analysts are responsible for data analysis and therefore the unit of analysis at each site are individual BI analysts. Hence,

the unit of analysis are individuals and not teams (Yin, 2014; Bryman, 2012). In addition, as mentioned earlier in the case context and background, to derive competitive edge, businesses have invested highly in BI&A and have employed data analysts for their respective domains. Both individual case site employs few people as data analysts, hence they constitute the unit of analysis for this case study.

3.4 Method of data collection

Initially, we started emailing and calling different business firms that we believed to be relevant in business intelligence and analytics case study research. After intense networking, contacts were established at IKEA and CDON in Sweden and their respective domains working with business intelligence and analytics that allowed us to conduct a case study. The case site and respective domains (departments) are relevant for our research question in business Intelligence and analytics, since their work entails day-to-day data analysis. Additionally, to our delight both case studies allowed us the access to specific domains and BI analysts after following proper authorization and protocol with BI analysts at BI-Innovation at IKEA and Business Controller domain at CDON.

Additionally, all the concerns such as ethical and the sensitivity of research study has been discussed and accounted for with both firms. In addition, since interviews were the primary source of data collection, these have been recorded using software, and transcribed later into text files. The unit of analysis are analysts working in their respective domains, thereby answers for questions are grouped for both case studies separately. In that way, the study is able perform depth findings and analysis for each case site (Yin, 2014). Also, cross case analysis is performed to find similarities and differences before presenting the discussion and implications.

Preparation and collection of the data:

The collected data needs to be of high quality (Bhattacherjee, 2012; Recker, 2013). We have practiced this by ensuring a fully functioning and adequate audio recording equipment were deployed, as well as simultaneously plotted down notes to act as a complement to the audio itself that can store initial thoughts and reflections during the interview process and that could be revised and reflected upon during the analysing process. The collected data must be able to confirm phenomena under investigation to allow the researchers to come up with a coherent answer to the research question. Even if it is not coherent, it must at least be truthful and handled with integrity (Bhattacherjee, 2012; Recker, 2013). Additionally, we have been checking coherency continually both during the interview process and afterwards to ensure integrity.

Following Protocols:

Since the interviews were semi-structured, it allowed for a greater amount of leeway for the respondent to express him- or herself freely, diminishing the risk of exhibiting reflexivity (Recker, 2013). We followed necessary protocols for this approach that had a predefined semi-structure and made sure to encourage the interviewees to speak their mind. The semi-structured method allows for an adaptive approach by flexible progression as new questions can be asked during the interview process depending on what is said by the interviewee (Recker, 2013). This was something that we made good use of by allowing enough room for

replies that we thought were relevant, interesting, and could add more value for our investigation. The interview process thus took the form of a conversation rather than a strict interview per say, that enabled a multidirectional approach with follow-up questions that were either of interest to the research question and topic directly, or to side topics that could provide extra insight or value to this study (Recker, 2013).

3.5 Data collection

3.5.1 Interviews

Interviews as such are a personalized method of data collection and to a various extent utilizes a standard set of questions (Bhattacherjee, 2012). Compared to other data collection techniques such as questionnaires, an interview scripts lends more leeway for the interviewer to contain special instructions or opportunities to record or plot down his or her own notations and observations in the interview. One big advantage of interviews, granted they are at least partially unstructured, is the possibility it presents to being able to follow-up the interviewee's responses with new follow-up questions for more clarification or if some unexpected but interesting point of observation unveils itself (Bhattacherjee, 2012; Schutt, 2011).

This is exactly what we utilized to the extent that was possible for us, as we allowed both ourselves and the interviewees to be flexible in the questioning and answering respectively. We also made sure to write down preliminary notes reflecting our thoughts on the spot. We as researchers also took on the role as instruments, as we constitute the data collection rather than an external object (Recker, 2013). Additionally, the Face-to-face interviews allowed us to have a direct point of concentration towards a respondent (Bhattacherjee, 2012; Recker, 2013).

The interviews in this research have been conducted in a semi-structured manner (Recker, 2013; Bhattacherjee, 2012), as semi-structured interviews are mostly dealing with general topics that can be seen and posed as themes (Recker, 2013; Schutt, 2011; Bryman, 2012). Therefore, the questions asked were expanded upon in an open manner to facilitate an open and thoughtful response from the interviewees, acting as a foundation for deeper questions that were not always pre-planned. The flexibility of this method is its main strength, allowing both authors as the interviewer and the interviewee to branch off in the interview process to find new relevant points of information. The sole structural part of this way of conducting interviews consists of the initial protocol we were based on, that helped us to guide the process by providing the necessary initial framework. Recker (2013) provides three other benefits specific to semi-structured interviews, the first of which is that they are not as encroaching as if one were to use a fully structured method since it facilitates a mutual communication between the interviewer and interviewee. The second benefit is that since it is more open ended in nature, it did not only help to provide the richer answers, but also the reasoning behind them.

Furthermore, Bhattacherjee (2012) outlines the role of the interviewer, to which he recommends five phases, which were carefully practiced while collecting interview data:

Preparing for the interview

The interviewer must be able to conduct the interview in an adequate manner, which results in a higher quality of data collection. Specifically, what this means is that the interviewer in question ideally has some degree of experience to leverage for the benefit of the data quality. Specifically, this entails knowledge of the interview process itself, study purpose, how the data will be stored and how to identify biases (Bhattacherjee, 2012). Since, both authors have conducted academic research in our previous degrees, we see ourselves as experienced enough to fulfil the roles of interviewers adequately.

Enable the cooperation of respondents

The interviewer should be able to provide enough incentives for the potential interviewee to make him or her willing to participate in the study. This includes being flexible according the schedule of the interviewee and being able to come to them (Bhattacherjee, 2012). Both authors have made sure to accommodate for the interviewees by conducting the interview on times that suited them, as well as respecting any other wishes or concerns that they had.

Motivate the respondents

Since it is the interviewer that is the driver behind the study and the interview itself, it is important that he or she can provide motivation to the interviewee by providing enthusiasm and be able to communicate the importance of the study. This also includes being able to motivate how the study can directly benefit them (Bhattacherjee, 2012). Both authors, motivated the interviewee by actively listening, showing interest and asking to elaborate more around interest, in that way both authors elevated interviewee motivation and interest.

Clarify confusions and concerns

Since objections and various concerns can arise unexpectedly by the interviewees, the interviewer must be able to think quickly to address any such problems that may come up. Likewise, asking relevant questions occasionally, when needed regarding such concerns is a good idea to make sure everything is in order with the respondent (Bhattacherjee, 2012). During the interview, the clarification and confusions were attend to and better explanation of question were presented when required.

Observe the quality of response

Body language can be used to the benefit of the data to better judge the data quality. According to Bhattacherjee (2012), the interviewer is therefore the best person to determine what information to keep track of and to disregard. This also since interviews take time to carry through, so a skilful person is more likely to make better use of the time needed than an unskilled one.

3.6 Data Analysis Method

According to Schutt (2011), qualitative data needs to be interpreted by way of text instead of numbers, as is the case of qualitative studies. This process allows for a method to find patterns, categories and various relationships through discovery and examination of the data. This by extension also means that there are no hypotheses or otherwise predefined sentiments.

The focus can thus be termed "emic", as it deals with representing the participants perspective and points of view that together make up the setting, instead of the etic focus, in which the setting and the participants therein are represented by what the researcher is able to bring into the study (Schutt, 2011; Miles et al, 2014). To conduct an adequate data analysis, it was important that the focus was lying on the case, meaning the cumulative interrelation of the setting and group being examined, rather that the separate parts that make up the whole (Schutt, 2011). Since the process of qualitative data analysis is reflexive and iterative, it does not lend itself well to focusing on a few select variables out of the total set of influences to test the relationship between these selected variables (Schutt, 2011). Instead, the process of analysis began with the collection of data rather than after the collection has taken place (Schutt, 2011).

Hence, a coding process employed to make sense of the data, a proper coding technique must take place. Coding is the act of organizing and categorizing the data into concepts and themes (Schutt, 2011; Bhattacherjee, 2012). Furthermore, coding also helps the researcher to connect data points to see influences, legitimations and corroborations (Schutt, 2011).

An example of coding using NVIVO is presented below, the process of open coding, axial coding and selective coding is further discussed in the following chapter. Also available at Appendix 5, IKEA

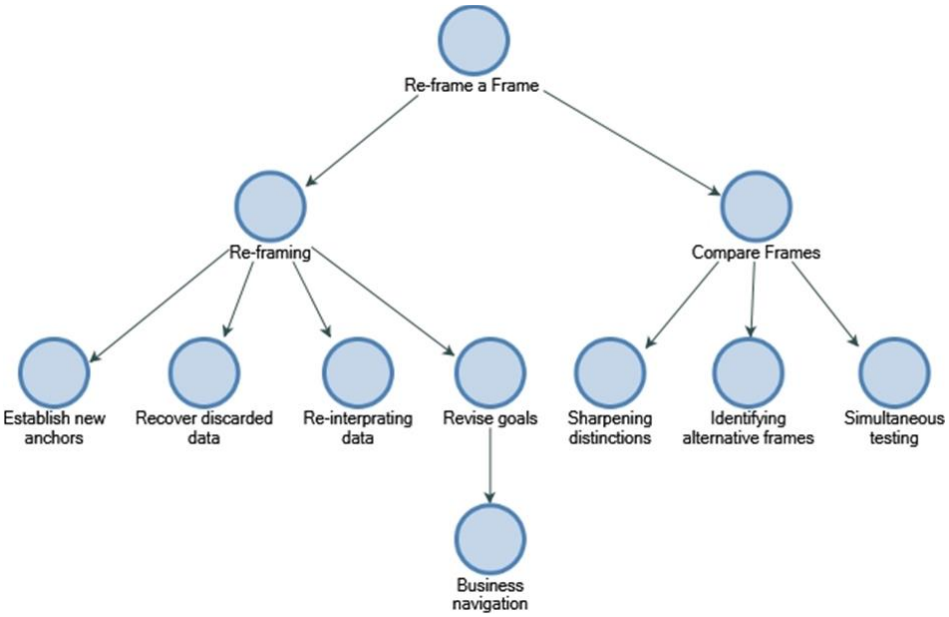


Figure 2 Re-Framing a Frame and Compare Frame, IKEA

3.6.1 Open Coding

First, we needed to 'open up' and name concepts in the data to uncover meaning and ideas in the interview transcripts that were being analysed (Benaquisto, 2008a; Recker, 2013; Bhattacherjee, 2012). Once, the interviews were collected the process of breaking down the data in segment commenced with the purpose of interpreting these segments using Nvivo12. Here Nvivo 12 initially deployed a naming convention (nodes) automatically, so that discovery and definitions of ideas could commence without much regard to how these are used in the end (Benaquisto, 2008a; Recker, 2013; Bhattacherjee, 2012). After concepts and ideas have been discovered, relationships between themes in the data could be explored using some manual process to verify and check if the tools had made the themes correctly. After some manual input, categorical dimensions were also being examined (Benaquisto, 2008b). In addition, labels were attached to objects or words in order to act as a representation of interpretation (Benaquisto, 2008a). However, all kinds of phenomena were classified in several ways, for example, comparisons between segments of data of similar concepts were directing to be classified together, which was commenced to reduce and sort out the data. The next step after the process, the building of more high-level categories would commence (Benaquisto, 2008a; Recker, 2013; Bhattacherjee, 2012).

3.6.2 Axial Coding

The next step in the coding process is the axial coding, which deals with developing individual categories (Benaquisto, 2008a). In this step, the data that was reworked in the open coding process was now put together so that they could be expanded upon in terms of dimensions and properties (Benaquisto, 2008b). It was in this step that we started to process and delegate concepts that stood out into relationships (Benaquisto, 2008b; Bhattacherjee, 2012; Recker, 2013), for example "Tasks and Goals" and "Discard Data" for example coding mind maps available at Appendix 8, CDON and Appendix 5, IKEA.

We approached the axial coding process according to the recommendations of Benaquisto (2008b), which means that we would look for answers for questions around certain categories, that we then would expand upon by asking question pertaining to, for example, frequency, location and by whom, as well as the consequence of that. This meant that we now had identified additional categories, which would enable us to identify emerging patterns (Benaquisto, 2008b), for example, "Gauge-Data-Quality" and "Seek-and-Infer-Data", for example coding mind maps available at Appendix 8, CDON and Appendix 5, IKEA.

3.6.3 Selective Coding

The final phase of the coding process that we did was that of selective coding. Here, explanations of phenomena were unrooted in a way that we could now identify a few central categories, to which the other categories could be linked and related to (Benaquisto, 2008c; Bhattacherjee, 2012; Recker, 2013). This helped us to get well-rounded story about what was happening, while also allowing us to understand certain sense making activities (Benaquisto, 2008c). Mainly, we identified higher level emerging concepts from literature, for example, "Connecting Data and Frame" and "Questioning a Frame Instantiation", available at Appendix 9, IKEA.

3.6.4 Cross-Case Analysis

The second level of analysis after presenting individual case site findings and analysis is conducted to do cross-case comparison to seek the similarities and difference between each case site, the IKEA BI-Innovation and CDON Business Controller domain (Stake, 2005; Merriam, 2009). The cross-case analysis requires at least two cases, which what we have in this study (Yin, 2014). Furthermore, the cross-case analysis can be performed by using word tables, which can display the data from both individual cases, but in a uniform framework (Yin, 2014). In this study we have made a matrix word table, using row to identify both individual case sites, IKEA and CDON in two separate rows, and then we used the some of the emerging themes mainly related to axial level categories to identify the similarities and difference between both case sites.

3.7 Software Tools for Qualitative Data Analysis

3.7.1 Nvivo for Analyzing, Organizing and Visualization of Qualitative data

Nvivo software tool have been employed for this process, as it is an adequate tool for coding. It contains the tools for identifying and coding themes as well as extracting concepts. Not only did this speed up the coding process, but it also helped research to ensure more meticulousness by making sure every potential theme and concept is thoroughly evaluated and validated. This was done by following the processes of open, axial and selective coding. The knowledge gathered from these processes constituted an increased knowledge and understanding of each individual part (Klein and Myers, 1999). Furthermore, Nvivo helped us with organizing the categorization of said themes and concepts by allowing for node allocation in a visual manner. Likewise, categories of data can be displayed and played out for an easy overview of the mapped-out categorizations, which further helps with the process of analysis, available for both case sites in Appendix 5, IKEA and Appendix 8, CDON.

3.8 Research Quality

The shortcomings of single case studies in particular are that there are no coherent test that can check for dependability (Riege, 2003). For this reason, an adequate research quality is imperative to obtain rigor. We have done this by following certain principles that match the type of research conducted. For this study, a single in-depth case study approach was employed, even while conducting two case sites. More specifically, a holistic case design with a single unit of analysis was used to examine the nature of the organization in-depth (Yin, 2014). In this study, this was achieved with our selected case at IKEA and CDON in Sweden with a minimum of three interview from each case site and specific domain. Also, as necessary, the four principles as outlined by Recker (2013) and Yin (2014) have been fulfilled in this research to the extent that is possible with single case studies.

Dependability: Achieved with the help of proper documentation to allow other investigators to follow the procedures taken in the case research (Yin, 2014). Without proper documentation, the possibility for replication would be non-existent. One such tool to ensure reliability is using a case study protocol and a case study database (Yin, 2014). All the relevant data for

this study is being attached from, Appendix 1 to 10, with proper structure so to allow the researcher to go back and identify or allows using the same methods of data collection and other processes.

Credibility: As guided by Recker (2013) that is concerned with if the researcher can provide enough evidence for proper interpretation in a qualitative data analysis. This has been achieved to some great extent by this study, by being careful when noting down decisions being made in the research process, as well as keeping an evidence chain.

Confirmability: outsiders can verify the findings in an independent manner by way of reviewing parts of the research data, such as inferences from qualitative data, interview summaries and conclusions (Recker, 2013). Because of this, we have made sure to be meticulous in our work process to enable and facilitate measurement validity by attaching all the transcripts and mind maps constructed using the qualitative data.

Transferability is the level of generalizability from a study to other settings or cases. We have made sure to adequately give detailed descriptions to enable other researchers to examine the characteristics of the context and for them to see how well these match their respective research fields (Recker, 2013).

3.9 Research Ethics

Since interviews are conducted in this research, it is imperative to be cognizant of any biases that can distort the results and findings. In the interview protocol, we have made sure that a neutral tone is maintained throughout, while also allowing the interviewees enough space so as not to lead them in any specific direction (Bhattacherjee, 2012). It is also imperative that biases such as trying to verify one's own already pre-existing ideas or prejudices or trying to make others commit to actions if they are in line with one's own personal interests (Schutt, 2011). The author also states that the pursuit for ethical adequacy is one of validity; the research needs to be justified and motivated in a way that gives the researcher justification in his or her research. This is important to avoid a subjective interpretation and respondent bias to which qualitative research is especially sensitive (Recker, 2013), especially considering the non-temporal nature of multiple perspectives (Bhattacherjee, 2012). We made a great effort to obtain adequate results by following and respecting the scientific method (Recker, 2013; Bhattacherjee, 2012).

As researchers, we are expected to follow general agreements that is shared by the scientific community, whether these are explicitly stated or not (Bhattacherjee, 2012). Some principles that we are expected to, and have followed, are

Voluntary participation and harmlessness: We have made sure that the interviewees have been made aware that they may withdraw from the study at any time without being pressured by adverse consequences because of non-participation (Recker, 2013; Bhattacherjee, 2012). This is mentioned in the consent form signed by interviewee.

Anonymity and Confidentiality: Anonymity and confidentiality has been guaranteed to the interviewees, when they desired. The first mentioned means that they cannot be identified by specific response, while the second means that while the researchers can identify a person's

responses, especially as is the case with interviews, the interviewees have been promised to not have their identity revealed in any form (Recker, 2013; Bhattacherjee, 2012).

Disclosure: We have been transparent to our subjects about the study, so that they could decide if they wished to participate. This includes who is conducting the study, for what, what kind of outcomes that are expected, and what the benefits of such study will be. Having this said, disclosing too much information can have an adverse effect as it has the potential to create bias (Bhattacherjee, 2012), so this is something we had to balance carefully by telling the essentials without revealing the questions that would be asked beforehand.

Analysis and reporting: Not only do we as researchers have an obligation of transparency to our subjects, but also to the scientific community as to how the data is reported and analyzed in the study. All findings, negative as well, are therefore included. Findings that came up by accident or chance need to be disclosed as such. Likewise, since it is considered unethical to fit the data into specific segments to prove or disprove a point of interest, or to take incomplete or partial data and claim them as valid (Bhattacherjee, 2012), this is something we have kept in mind and avoided.

Also, Klein and Myers (1999) talk about The Principle of Suspicion, which concerns the interpretation of meanings to avoid distortions in the collection of narratives. This principle says that there are multiple layers of interaction going on that can distort the beliefs, consent and attention of the people within that context. This approach tells the researcher to not only try to understand the meaning of data, but also to interpret the social aspects behind the words of the relevant actors that is characterized by interests, power structures and resources that is supposed to meet the goals of actors (Klein and Myers 1999).

For the ethical considerations, we also follow the, *"Principle of Contextualization and Principle of Interaction between the Researcher and the Subjects"* (Klein and Myers, 1999). The focuses on the importance of considering the interviewee in a proper social and historical context to enable readers to see how the situation occurred under the issued examination. The last mentioned partly focuses on the inverse of the Principle of Contextualization, in that researchers put as well as the subjects are put in a perspective of historicity. Klein and Myers (1999) argues that the information is produced as a result and part of the social interaction as opposed to just sitting there independently of any influence. Participants are thus interpreters in the same capacity as the researchers themselves, as they broaden and alter then viewpoints and actions as they appropriate IS-related concepts. Klein and Myers (1999) thus also argues that what this ultimately means is that the researchers' preconceptions about the interviewees affects the documentation and organization of the data, which would mean that the research materials are socially constructed. This kind of interaction will present itself in connection with the performed interviews. Another principle that we have followed in this research is that of Multiple Interactions. As researchers, we need to recognize that people are highly dynamic, meaning that it is possible that narratives and interpretations will be expressed in various manners, which in turn can lead to different event sequences (Klein and Myers, 1999).

4 Findings and Analysis

The study set out to investigate BI analyst to understand how they generate insight and give meaning to data. The study conducted interviews and collected findings from our two individual case sites. Both case site findings were independently transcribed and open-coding was performed using NVIVO 12, to bring out recurring themes, patterns and their relationship between them, such as, data, BI&A Tools and others. In addition, axial coding performed to create categories, such as, tasks, goals, source of data and types of data among many others to identify emerging patterns. Later, selective coding was conducted to identify higher central categories and to link these categories with related ones. This method allowed us to understand the central themes around insight generation from data, which then guided the study towards the literature and theoretical framework (Miles et al, 2014).

Initially the findings and analysis for each case site is presented independently and then cross-case synthesis/analysis is conducted to bring to surface the similarities and differences and other important insights using word table matrix. Additionally, the coding process (open-coding, axial-coding and selective coding) which was processed and documented using NVIVO 12 are available in, Appendix 5 and 8 for both case sites.

4.1 IKEA Case Context

In this thesis, we have employed the emic perspective to analyse this framework. More specifically, this perspective pertains to the viewpoints of the participants and according to their terms, as opposed to from the viewpoint of us as researchers (Schutt, 2011; Merriam, 2009; Willis, 2007). In other words, the interviewee's meanings and interpretations of the events is captured and analysed.

A frame is a viewpoint or perspective which can take various shapes, such as maps, stories, diagrams or scripts (Klein et al, 2006b). The frames themselves are defining the data, while at the same time also defining what constitute as data (Klein et al, 2006b). The frames work in tandem, building and elaborating the overall framework by adding details and inquiring the frame, as well as allowing a BI-analyst to employ scepticism (Klein et al, 2006b). As can be seen in Figure 1, the main frame cycles are elaboration of a frame, questioning the frame, as well as re-framing a frame (Klein et al, 2006b). Each cycle has its own sub-cycles and procedures that further defines tasks and mindsets within each cycle (Klein et al, 2006b). This model has then been used in a BI&A-context to identify the mindsets and procedures of BI-analysts when conducting their data related tasks in order for insight to be generated. Finally, we have added the identified tasks derived from our interviewees in the first case analysis to the model.

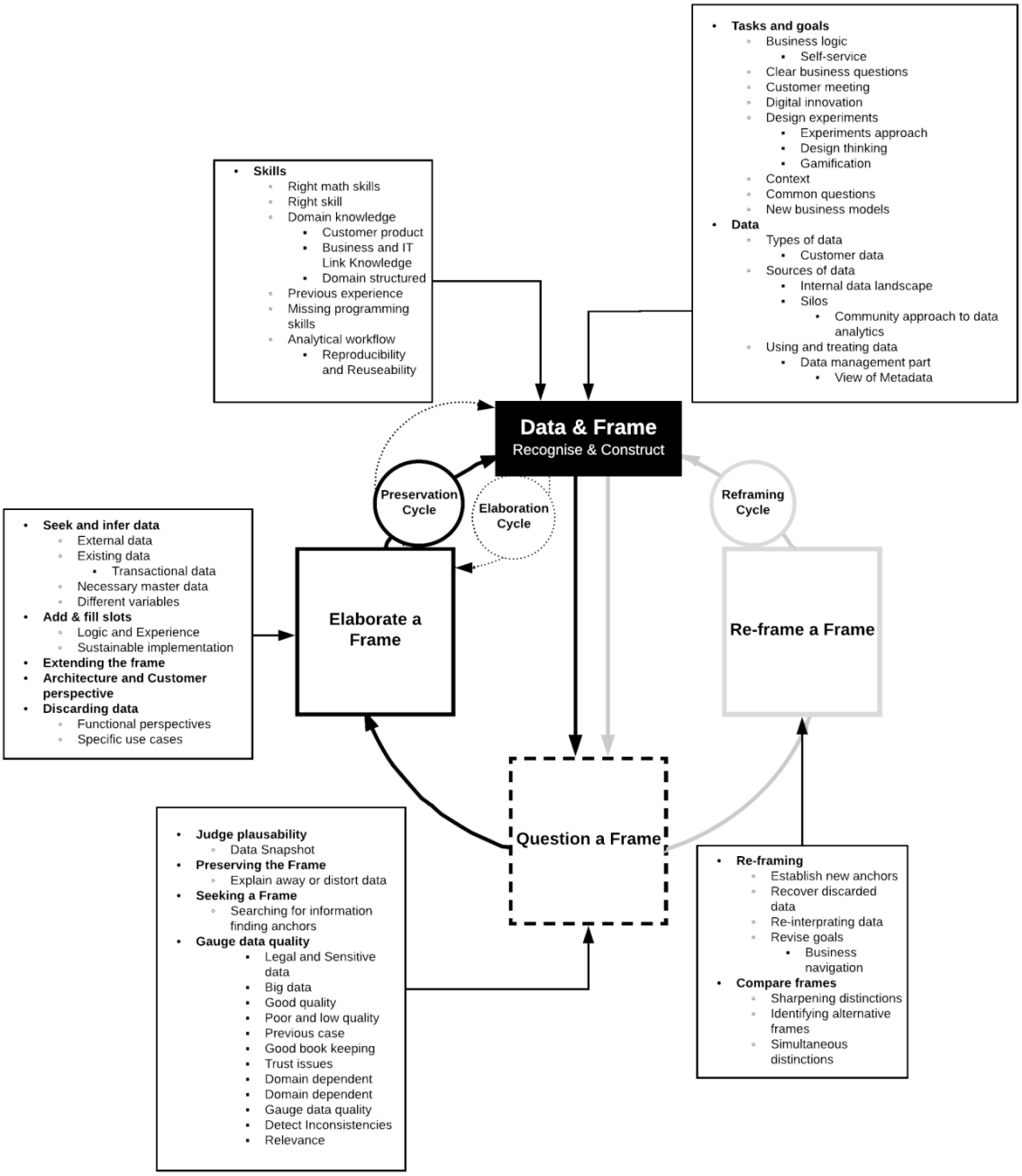


Figure 3 Data/Frame Model of BI Context-IKEA

The finding and analysis presented here follows the structure that emerged from the data while coding process was performed, available at, Appendix 5. The findings are analysed using Data-Frame Theory of sensemaking in the BI&A context. Also, the interview transcript data for the BI analyst are available at, Appendix 2, 3 and 4.

The initial findings indicate that there is indeed understanding and use of business intelligence and analytics at IKEA, and that BI-analyst that we interviewed are the core of this functions, as stated:

"We have a full range of tools. We have the kind of business office things, we have the more BI-tool like Cognos and QlikView" (IKEA BI Analyst, 2018).

Theses finding are in line with BI&A literature, such as, on-time decision making, predictive analysis and reporting among others (Watson and Wixom, 2007). Furthermore, the findings also indicate the strategic alignment of IKEA with its BI&A-tool provider for their BI&A functions, as stated by the BI analyst,

"We work with a lot of big vendors on the software side from Microsoft and IBM and also smaller ones like Neo4j for example, they do graph databases" (IKEA BI Analyst, 2018).

The essence here is that the BI-analyst beliefs in the importance of information technology and its alignment with IKEA's business strategy (Watson and Wixom, 2007; Elbashir et al, 2008). Also given that the BI&A-tool vendors are big firms like IBM and Microsoft, this goes in line with focus on enabling IT to support organizational business strategy mainly associated with organizational transformation and the implementation of new business models (Watson and Wixom, 2007).

Furthermore, the finding and analysis presents skills, previous experience and knowledge of a BI-analyst as a dominating and prominent theme around the data-frame theory of sensemaking (Klein et al, 2007), which was presented initially and also discussed throughout, when data-frame-theory of sensemaking was used as an analytical framework to explain the findings in IKEA business intelligence context.

4.1.1 The role of Skills, Previous Experience and Knowledge

Skills are the most important in making the sensemaking possible, such as the mental activities in sensemaking where clarification and removal of ambiguity is necessary (Namvar et al, 2018 cited in Weick et al, 2008; Russell et al, 1993; Brown et al, 2008; Dervin, 1998). More specifically, the role of skills in BI&A is about searching, processing and organizing the similarities and differences from data sources in the right way so to maintain the quality of sensemaking which affects the quality of knowledge that will be produced, and the outcome of decision predicated on the extracted knowledge (Namvar et al, 2018 cited in Weick et al, 2008; Russell et al, 1993; Brown et al, 2008; Dervin, 1998). Similarly, in line with sensemaking literature, as stated by BI-analyst below; they see the process of information searching, processing and organizing as analytical workflow with proper exploratory analysis.

"Through a proper analytical workflow with proper exploratory analysis and so on. So that what is needed that is probably missing in many cases today. Some places do it do it pretty well but then in general I would say it's an area where we need to do some work" (IKEA BI-Analyst, 2018)

Additionally, BI-Analyst stated in interview quote below that the analytical workflow is needed to make sure they are analysing the right data, on which they can take best assumptions or decisions. The analyst believes this is worrisome, since a lot of factors are in play, such as: 'who did the initial analysis?' or 'Where is the proof?'. These issues as per the analyst due to the non-modern analytical workflow having consequences of reproducibility and reusability.

"Are we analysing the right things, are we making assumptions or decisions on the wrong things? That can be quite a worry, especially when you have different numbers and anything; which one is correct? Who's done the analysis on this? Show me the proof. That's a little bit missing. There's a big mistrust, I think, in a lot of the reports that come out, because we don't have let's say, the modern analytical workflow where we need to have reproducibility and reusability and so on. That's missing. It's very Excel driven, as I said to you, so if somebody

has some recurring reporting that they're doing, and they change jobs, then it's somebody else's job to sort of reverse engineer that excel file and look at all the formulas and everything and try to understand it. It's not a reproducible product. Again, it's part of our journey, deeper into analytics. But today, that's where we are" (IKEA BI Analyst, 2018)

Furthermore, the reproducibility and reusability are in line with literature of sensemaking in terms of having quality frames (dashboard, reports etc) and right data sourced and produced to support those frames Klein et al (2007). Hence, existing data and frame understandings to achieve characteristics and attributes of trust and quality results in reproducibility and reusability of it when needed by the BI analyst.

In addition, the findings indicate not only a modern analytical workflow understanding is needed, but also the ability to understand that the domain in which the BI analyst performs his/her work is important. As quoted by the BI analyst below:

"Some key components and foundation which is maybe you talk about the link between business and IT. I think as long as we talk about business and IT as two independent bodies,, then that's not helping. We have to have a more federated approach where we have business people that understand technology, and technical people that understand the business needs. So, you need sort of one foot in both camps almost, if you want to be successful. That's an important point to bring out. If it's such a reliance on technology, whether is data warehousing, whether it's tools, platforms, whatever. So there's a very close marriage there that's needed" (IKEA BI Analyst, 2018).

The domain knowledge importance by the BI analyst is in line with the sensemaking literature, as mentioned by Klein et al (2007), although professionals and experts prefer a functional understanding but are likely to consider an abstract understanding to expand competencies in other areas to achieve practical approach towards their task and it adds to their understanding of what is going on (Klein et al, 2007). Therefore, sensemaking results in understanding of what is possible and what is not using a wider repertoire of frames so that a potential candidate (frames) can be of use, when needed by the BI analyst (Klein et al, 2007).

Furthermore, the findings from BI analyst as given below indicate that IKEA analyst do have domain knowledge, but the emphasis is also mainly upon analytical skills, capabilities such as, math and statistical knowledge along with some technical knowledge mainly relating to programming and coding is seen as missing in the area of data analysis, as quoted by the BI analyst:

"So, we have a lot of business domain knowledge throughout all of IKEA. but when you come to the other two big areas of this field, which is more of the analytical skills, so do we have people with the right math skills and statistics knowledge and so on, to be able to do this analysis? And then do we have the technical skills to be able to, you know, maybe there's programming or some coding or even just as simple as how do I connect to a database? That sort of skills is sort of, a little bit missing. It then becomes a bit difficult to know how we actually analyse data properly" (IKEA BI Analyst, 2018).

The expertise in maths, statistical and programming is in line with sensemaking literature. As pointed by Klein et al (2007) sensemaking is beyond the comprehension of stimuli only, it is also about detecting regularities closely or connecting dots/relationships to find/discover and predicting future states so to prepare, identify problems using variables event or situations. Hence, we believe that through using proper skills, whether they are math, statistical or programming skills (coding), the BI analyst is in good position to analyse data in much better way.

In addition, the findings indicate, the BI analyst place great emphasis on previous experience and knowledge, as pointed out by BI analyst:

"I'm nearly 20 years in IKEA, and my role is BI and Analytics. I'm working across a number of different areas in business, so particularly in the business navigation as we call, it, area. We're dealing with financials and so on. And then I've also worked with some of the IT components like data warehousing and so on, so I have a pretty good understanding around of the BI world" (IKEA BI Analyst, 2018).

and,

"I've been working in the stores in the UK for 10 years and then probably the last 10 years working with BI analytics. So that's my area. And I would say even though I'm based in the business navigation area, we take a cross-functional view of analytics, especially within this program that we've been working on for the last two years now, so it's more about trying to drive innovation in this area" (IKEA BI Analyst, 2018).

The previous knowledge and experience as indicated by the BI analyst is in line with the literature, as expert having richer repertoire meaning that they have better and richer mental models (mental activity), such as, wider understanding, sharp differentiation, in depth, more plausible awareness of context and are insightful due to the previous experiences and knowledge frames from which they are able draw upon (Klein et al, 2007).

In summary, the finding and analysis presented in this section mainly indicates that, the skills, be it mental analytical workflow thinking, or practical understanding of maths, statistics and programming languages, and business or it domain knowledge, they are very important elements in BI&A. Also, the study finds that these characteristics are prominent and present in our detail findings and analysis as we apply the data-frame-theory of sensemaking to explain the findings we got from IKEA BI&A case context.

The next chapter starts by presenting findings that are analysed and explained using data-frame-theory of sensemaking by Klein et al (2007). Also, since the questions were guided by the theoretical framework of data-frame-theory of sensemaking, the study presents the findings gathered through the interviews in structured manner to reflect back on different part of the data-frame-theory and followed by analysis.

4.1.2 Forms of Sense Making

4.1.2.1 Connecting Data and Frame

4.1.2.1.1 Tasks and Goals

The initial findings from BI analyst indicates, that there are vast opportunities and in different domains within IKEA in terms of data analysis requirements and opportunities, as per the BI analyst:

"So, the fun part working at IKEA is that there is a still vast amount of opportunity. So, some of the problems we face right now is that data is seen from different perspectives and we need to improve what data we put in which context. So, the context is the crucial part to work from to see how it can support the business model" (IKEA BI Analyst, 2018).

However, the context in different domains is referred to clear business questions in relations to supporting the business models, also as mentioned by the BI analyst:

"Start off with clear business questions and then get the right data to answer that, and then go through a proper analytical workflow with proper exploratory analysis and so on. So that what is needed that is probably missing in many cases today. Some places do it do it pretty well but then in general I would say it's an area where we need to do some work" (IKEA BI Analyst, 2018).

The findings are clearly in line with data-frame-theory, that suggests people usually comprehend, understand and realize the events, or problems that are triggered by unexpected revelation, which then makes people doubt the initial understanding and will require from them to monitor and address issues (Klein et al, 2007). Additionally, the BI analyst gave importance to data improvement and the selection of right data for the right context that will support the business model. Likewise, in line with the literature, we find that the information task of sense making is to understand knowledge area, situations and problems or work task of information actions that are relevant (Zhang and Soergel, 2014).

However, besides the initial comprehension, the findings from BI analyst also indicate extension of their comprehension of business issues, as stated by the analyst:

"So, it's more or less how we can increase our customer meeting and enhance that with digital components. So, it's online or in the store or on your mobile" (IKEA BI Analyst, 2018).

Here, as in correspondence with literature, the BI analyst is going beyond the day-to-day problem detection by extending their understanding and connecting-the-dots to make new findings (Klein et al, 2007; Yi et al, 2008). To further elaborate on this area, the findings indicate that this process of insight generation is mainly conducted using experimental approach, as stated by the BI analyst below,

"Compared to many other areas, the innovation department we work a lot with an experimental approach. So, our approach to the task in that sense unless we have every focus on problem, and then trying to create solutions for solving these problems, but instead of creating the solutions we design experiments" (IKEA BI Analyst, 2018).

By experimenting, as in line with the literature, BI analysts are discovering and mapping the relationships to see the current state of problem and then create experiments before solutions are created, to predict future state, by preparing beforehand so to be able to identify problems that may arise, by verifying variables in a specific situation or event (Klein et al, 2007).

In addition, at the core of solving tasks, goals, business questions/problem or innovation is also the use of data, as stated by the BI analyst:

"If it starts with the right question, and it might be a problem area like a business problem or an issue somewhere, and it might have maybe 50 related questions that we need to answer. Then of course the next question is; okay, now we are clear on what the issue and the questions. Do we have the data to answer those questions?" (IKEA BI Analyst, 2018).

Here, the findings indicate are in line with literature that when generating insights or sense making is commenced, it is a process where clarification, removal of ambiguity and, or uncertainty is needed by searching, organizing similarities and differences from data sources (Namvar et al, 2018 cited in Weick et al, 2008: Russell et al, 1993; Brown et al, 2008; Dervin, 1998).

In that way, it also means that, tasks and goal-directed interpretations of decisions making are established along with the search of data, as stated by the BI analyst:

"I think when you talk about innovation, and I work quite a lot with on the Digital side of innovation, it is so much around data. And this type of experimental approach that we have requires so much speed because we want to have iterations of experiments in order to go somewhere, and that of course requires a lot of feedback in terms of data and then in terms of speed in that data connection as well" (IKEA BI&A Analyst, 2018).

Hence, when clear frames are established, then right data is imminent and crucial for bringing to reality and execute those frames, therefore the next findings and analysis focus upon data input.

4.1.2.1.2 Data Input

As established in previous findings and analysis, once the objectives, tasks and goals are set, then BI&A analyst consider data inputs to connect and feed frames. This goes in line with the literature, connecting data with frame or frame with data is the next process (Klein et al, 2007). Where data represents the interpreted signs of events and frames are used to explain the data or to put it differently frame are accounts of data, as stated by the BI analyst:

"Do we have the data to answer those questions? In many cases we do if it is transactional data that we want you to analyse, but in many cases also we don't have that, and I think today's big picture is we always look into our internal data landscape to see if we have that. But we are moving, and employee (X), he would be able to explain a lot more. But what data do I need to answer this question." (IKEA BI Analyst, 2018).

The findings from BI analyst indicates that sourcing data is not the only task in hand but also working around the challenges associated with it, such as quality issues, right data source, right data type and the overall management of data. In addition, for BI analyst, the source of data is scattered in the internal data landscape of the company which means different silos are holding the data, as stated by the BI analyst further:

"So you end up with lots of difference. And if you take sales reports, we must have hundreds of sales reports and if somebody wants to say "well, what are my sales for last week", they could look at five or six different reports and all would get a different number. So, this confusion is bred out of a lot of the needful for information but hasn't been addressed I'm saying in the best way. We're very silo Driven, we have different functions create their own version of the truth, as it were, and its part of the work we're doing" (IKEA BI Analyst, 2018).

Additionally, to come over the silo driven approach the BI analyst wants to create a community approach to share sharing solutions and ideas that are built elsewhere in the organization and to make it easier to help BI analysts. This goes hand in hand with the literature, as existing frames, such as, stories, scripts, maps (reports/dashboards) and or other type of structures can be used in the process of sensemaking because frame are explanatory frames of the account of the data, where data can be made to fit into a existing frame to make sense out of it (Klein et al, 2007). This is exactly what is being point out by one of the BI analyst, as stated:

"Now is to try to break down those silos and take a more community approach to data analytics. And actually, it doesn't really matter who builds, but just share it. So, if we have a good solution build somewhere, then share it. So, this is a little bit of what we're facing right now. And of course, a lot of movement in the business; we've been pretty stable as a bricks and mortar retailer for a number of years. Now it's a big change to do e-commerce and multi-channel thinking. So, it's a completely new business model, really. So of course, data analytics has an important part to play in that, and our business users have a lot of the same questions, and so part of our innovation part trying to see where we can make life easier for people, I can say it simple as that" (IKEA BI&A Analyst, 2018).

However, sometimes the existing frameworks may not work due to some reasons, as mentioned in the literature, data and frame are two entities they must be balanced in situations when data does not fit the frame, or the frame needs replacement with the relevant ones or while using the existing frame, new data inputs might be needed (Klein et al, 2007). Same is indicate in the findings, as BI analyst states:

"Change our mentality from "okay, I need a dashboard and so we start a project for two years, and then by the time the dashboards built, then the business has changed". So, we want to move away from that" (IKEA BI Analyst, 2018).

Additionally, the findings as discussed previously also goes in line with further elaboration in literature in terms of sensemaking to be expansion of signs by searching for frame where within the signs will fit together and will make sense, this can be a continuous cycle between data and frame as explanations (Weick, 1995; Klein et al, 2007).

Secondly, using and treating the data while connecting data and frame is equally important as finding the sources of data, since the quality of knowledge depends on the data and decision predicated on the knowledge (Namvar et al, 2018 cited in Weick et al, 2008; Russell et al, 1993; Brown et al, 2008; Dervin, 1998). The literature mentioned also goes in line with the findings from BI analyst in regards ensuring to hold right data, the integrity of data, the consistency of the data and of the storage of data, as stated:

"We need to change the business model and we have to find ways, especially from the customer data side. I think it's pretty good that our transactional systems and our enterprise data warehouse is pretty robust, but it's the unstructured data, as they call it, or the external stuff that; how can we get off that, and make sure we are getting the right data. That's a bit of a challenge now" (IKEA BI Analyst, 2018).

Furthermore, when considering data is the findings indicated that it is also about the integrity and the consistency of data, as stated by the BI analyst in relation to data landscape, as stated:

"One of the challenges is very much on the on the backbone on the backend side; how we how we treat the data, how we treat the integrity of the data, the consistency of the data, and how we spread the data around in the IKEA landscape. It's not an easy task" (IKEA BI Analyst, 2018).

4.1.2.1.3 Summarizing Connecting data and Frame

The overall findings in relation to connecting data and frame indicate that, BI analyst requires clear business questions or experimental approach, which we can call frame of understanding or business solutions in BI&A context. In addition, the role of right data, from right source with consistency and integrity is needed for the frame established. Also, to be able to spread the data across organization without having to face data quality issues, by building a community approach towards data analysis and sharing of established solutions.

Furthermore, in the next chapter the study presents findings and conducts analysis by using elaborating a frame literature from data-frame-theory (Klein et al, 2007). The Elaborating a frame is needed when there is a need to add further detail (data) to extend already established frames (Klein et al, 2007), as it was discussed in the previous findings by the BI analysts, about having clear business questions and frame.

4.1.3 Elaborating a Frame

Once data and frame are connected than BI analyst mainly focus on elaborating a frame by adding or filling slot and discarding data until the final candidate frame emerges. In addition, the skills set as discussed in the first chapter of findings and analysis is partially present in each cycle of the Data/Frame Theory and widely discussed in the specific action taken by the BI analyst, so as to have better understanding that skills are part of each action and isolated.

4.1.3.1 Adding and filling slots

As discussed in the literature, when elaborating the frame people may extend or elaborate when new surprises or anomalies emerge by adding and filling the empty data to find relevant explanations (Klein et al, 2007; Pontis and Blandford, 2016). The findings are in line with the same, as stated by the BI analyst:

"The idea behind that is that it's pure logic and that also experience on top of the people that are making this decision, because let is let's say we have an example of chair that we're selling, and we put different price tags on the chair whether you have your loyalty member or a regular customer or maybe there is a discount on it. And let's say that would be, as an example, five different prices on this chair, but the actual case is requesting three of them. Then we will say "ah, but it's probably only a matter of time until that case will be evolved looking at the other two". So, in that case we take all five" (IKEA BI Analyst, 2018).

The findings also indicate that when adding and filling data slots, pure logic and experience will can help people that will make important decisions. For example, in case of chair price example as stated above BI analyst, IKEA has different price tags due to different customer segments and promotions, but the actual case, which might be an IKEA store in Helsingborg is only requesting a promotional price on that item. In any case all of the data input will be considered based on BI analyst previous experience and logic (domain knowledge) as the requirements for a particular price may come up anytime, hence the extra data is still seen as suitable as a data input or fill empty slots or allowing BI analyst to extend their frame of understanding when needed.

Additionally, as mentioned in literature by Klein et al (2007), sensemaking will continue if there are unexplained key data elements or key components of a frame, and should more perceived benefits for further exploration arise, the sensemaking make continue and expand to seek and infer data.

Furthermore, in terms of adding the filling data slots, the findings also indicate the sustainability characteristic of elaborating the frame, as stated by the BI analyst:

"Modern integration concepts we are applying because we know from the history that as large company, when we build integrations, they will stick for quite some time, so they need to be what we call it a sustainable implementation of that" (IKEA BI Analyst, 2018),

And,

"if we go to the traditional side of BI, we would transform the data into dimensions and facts and by that you would be able to build your data models and combine different data sets "(IKEA BI Analyst, 2018).

Meaning, that data integration, and concepts (frames) applied to it, should remain sustainable for some time, as it is hard for a large firm like IKEA to change or build dashboard or reports from the scratch in very short period, hence sustainable implementation is crucial for BI analysts. Likewise, this goes in line with the literature, the motivation behind sensemaking may decrease, when a frame (concept) is stiff and unbending (Klein et al, 2007).

4.1.3.2 Discarding Data

The finding also indicates as stated below by BI analyst, by adding and filling data slots is not the only process in sensemaking, but also the need to discard data due to some business requirement of reducing cost, processing or the use case. While elaborating the frame the BI analyst places a transaction example, where the use of data is limited to numbers and not images and will not be needed in that situation, hence will be discarded because it may cost and add strain to processing.

This goes in line with the literature, when elaborating the frame, people may define strategy by looking at new sources of data/anchors, because the data currently in use in a frame may hinder or may be irrelevant for current situations or problems and hence can possess conceptual strain for people (Pontis and Blandford, 2016).

"It's a really good question. So, we have had, up until now I would say, a principle of taking in more data than the actual case has required. however, due to cost, due to processing and so on, we don't have a way to, let's say, take an entire system of data. So that has not been our goal either. But we have consciously, let's say, have a principle to discard data. for instance, as I can mention just as an example where I work here for the use cases, is that, let's say, you have a you have a transaction that includes the number of attributes, and those are pretty much integers or that kind of type, and then you have an image. So depending on how big the size is of that image, maybe that image is not needed for this specific use cases right now. So we discard the image for now, because it might we might have a better storage optimization for images. So that's how we kind of think when we disregard some assets" (IKEA BI Analyst, 2018).

Additionally, in the case of IKEA as stated above, the processing of more data than needed is seen a conceptual strain when making sense out of data and besides that, the cost is also considered with respects to storage issue. Moreover, also very important and interesting aspect is line with the literature; the data elements are not the perfect representation of reality but are framed and depend on people goals and experiences (Klein et al, 2007 cited in Medin et al, 1997 and Wisniewski et al, 1994). The same is argued by BI analyst as stated above, it is not only a concern of cost or processing strain but also the use case of it, as mentioned the analyst will discard images since there is no need for it in a specific case.

4.1.3.2.1 Summarizing Elaborating the Frame

Elaborating the frame is about adding further details to frame to clarify ambiguities, surprises or extend the frames to find explanations. The role of skills and previous experience and domain knowledge is evident here, since experts tend have a richer repertoire and is the same case with senior BI analyst working at IKEA. Secondly, when elaborating the frame, the role of discarding data is also pointing at reducing costs and lowering strain on processing along with if a certain type of data is needed in the use case, or if not then discarding the data is appropriate.

4.1.4 Questioning a Frame

Questioning the frame is highly dependent on skills and expertise of a BI analyst, as mentioned in the literature review, when a person faces fundamental surprise, finds a framebreaker or has a differentiated frame are mainly triggered when inconsistent data, anomaly is detected, or expectations are violated (Lanir, 1991; Feltovich, 1984; Klein et al, 2007). The finding from this case are in line with literature, the BI analyst also indicated these aspects in terms of the quality of data, relevance and plausibility of data which will be presented and analysed below, using different sections to have in depth analysis using Data/Frame Theory of sense making.

4.1.4.1 Data Quality, Relevance

As mentioned in the literature, when questioning the frame or initial understanding of a situation or event might change depending on the data quality in terms of inconsistency and accuracy of it (Klein et al, 2007). Similarly, the findings from BI analyst indicates the same as stated below, the quality of data might get affected because customer do not tend to update their details, and even if they do say, data might take already by BI analyst might be wrong:

"No, I think it relates to two things the quality of the data; at IKEA we have tons of customer data around the world but it's also very poor quality. If you look at customers' home addresses and so that it's updated quite frequently. We can't really keep that up to date since it requires the customers to actually update it. So, there's a lot of quality issues. And then on the other side you have more of an accuracy of the data, so quite often you when you design experiments, experiments design is extremely difficult to do in a business environment. In a scientific environment it's easier, I would argue, because then you can control the experiments better. In the

business environment there are often very many variables which you can't control. The data generated sometimes isn't accurate because the design of the experience was actually wrong" (IKEA BI Analyst, 2018).

Furthermore, to elaborate the above findings, IKEA also relies upon customers with personal information and if the data is not updated on time, the accuracy of data is questionable and also the consistency of it. In addition, since IKEA performs a lot experiments, based the initial frame or concepts as discussed earlier in the findings and analysis, the initial frame experiment produces inaccurate data for BI analyst and also since the variable are often too many, which means it cannot be controlled by the BI analyst.

Moreover, as mentioned in the literature, when questioning the frame, the unstructured nature, source of information and its accuracy, can affect greatly how analyst frame their understanding, and also process is lengthy, which will put strain on BI analyst to make sure the quality of data is maintained, hence the need to gauge quality of data is important (Pontis and Blandford, 2016). Similarly, the findings indicate the same, as stated by BI analyst below:

"Our transactional systems and our enterprise data warehouse is pretty robust, but it's the unstructured data, as they call it, or the external stuff that; how can we get off that, and make sure we are getting the right data. That's a bit of a challenge now" (IKEA BI Analyst, 2018).

In line with the literature and the findings further indicate that BI analyst is affected by IKEA's internal sources and external source as well (the other systems). The BI analyst points out that, although internal systems produces good data they also need to work with external systems for sourcing data, which may then pose trust issues and thus requires from BI analysts to maintain exploratory analysis to identify consistency and accuracy of data. As stated by the BI analyst:

"I think within our own systems, it's like, what's good data quality? But it's good enough, is the typical answer there. But because a lot of the other systems it's hard to put that trust into those sources, know? Should I use that source, or should I use X or Y? Again, this is where the exploratory analysis. what sort of variation in the data do I have, and what can I trust?" (IKEA BI Analyst, 2018).

Beside data quality issues, when questioning the frame, the findings also indicate the need for BI analyst to understand the business vocabulary or value creation (business understanding) of data and is seen a big challenge for BI analyst at IKEA. As stated by the BI analyst:

"So instead of just taking what the data you have, that might be one case, but very often it ends up that you need to go back and analyse it to see if this is now actually the right data for the right purpose. So that is one of our keys… I would say problems actually, and the whole, let's say, vocabulary or business understanding of the data is a big, big challenge not only for IKEA I believe, but for any large company" (IKEA BI Analyst, 2018).

The business vocabulary or understanding goes in line with the literature. By seeking new frames through information and finding anchors, which will support the propositions (Klein et al, 2007; Pontis and Blandford, 2016). Meaning, is this the right data for the right purpose and, secondly does it create value and is understandable enough to the BI analyst, so sense-making can progress and improve, for example, 'what can you do with this data?', what business value is producible.

Another interesting insight indicated in study findings is of the data profiling, which goes in line with literature discussed, (Klein et al, 2007), when questioning the frame. The findings indicate, as stated by the BI analyst, depending on the context (event, business problem etc) this might be good or poor quality. For example, even the existing data be gauged based on its relevance to the context, because the company constantly faces new situations and problems

and thus requires from the BI analyst to verify in the initial step, the worthiness of the data at that moment in time.

"The first thing we do is the data profiling on the data, because depending on the context, the data might have bad quality or good quality. And also, we need to do the data profiling even on the existing data, because if it's a new context the quality might be okay for the previous case but not for the new case. So, we try to do that as an early step to find out; are there now a good likelihood that this data that will actually help us in this case or not" (IKEA BI Analyst, 2018).

4.1.4.2 Judging Data Plausibility

When questioning the frame in terms of quality of data, the findings indicate that BI analyst as stated below, will usually take a snapshot of data and to conduct the data profiling, which we discussed above with regards to context and where it is needed and why. This method of questioning the frame is of plausibility by reducing the amount of data for analysis is in line with literature in terms of experts have skills in using BI tools to be able snapshot data, from experience understanding the business value of it, creating better models by digging deeper into selected data points (Klein et al, 2007; Pontis and Blandford, 2016). In that way BI analyst is conducting a thorough analysis using a snapshot of data by reducing the variables that may affect the analysis in terms of what was discussed earlier in the analysis, the processing time is reduced, it better adapted to the needs of business and data storage cost are lowered and of course allows BI analyst to generate relevant insights from data.

"Usually we take like an… we call it an extract or a snapshot of data, and then do the data profiling on that and that then that can be iterated depending on which dimensions you would be looking at and how large the data set is, of course. So that is something we do at every time, I would say" (IKEA BI Analyst, 2018).

Furthermore, since questioning the frame involves mental skills and previous knowledge as discussed earlier (Klein et al, 2007; Pontis and Blandford, 2016). The BI analyst is also of the view that as stated below, that frequency of data is sometimes more important than the quality of it. Here the emphasis in the context of need and requirements by different domains within the company. For instance, as mentioned by the BI analyst, a lower quality but frequent and big data is acceptable in certain situations, because the frequency is more relevant than the higher quality. However, on the other hand, when it is more about financial data, the frequency is compromised because the data needed goes to the books for quite some time and must be correct. In addition, the BI analyst means that financial audits could be performed to check if the data is correct later and thus requires from them to maintain accurate records of the events and in that way for BI analyst the domain and context specific data quality issues are very important:

"There is the life cycle of that particular system, it is the ability how to integrate and what frequency that data that can be delivered. So may so there needs to be a correlation to the business case; how frequent you need it versus the quality, for instance. maybe it's better to have low quality and lot a big frequency if you use the samples of the data, so like in big data for instance or if we actually for financial records for instance, then you might not need it so fast, but you really need a high quality of it. So because it goes to the books it needs to be correct. So it depends a little bit on the domain and also if it's legal case, of course and so on, as well" (IKEA BI Analyst, 2018).

In addition, the plausibility of data is further assured by ensuring the consistency of the data. As stated below by the BI analyst, the statement goes in line with the literature pointing out that frames can be questioned because of inconsistent data or anomaly detection or violated expectancies (Klein et al, 2007; Pontis and Blandford, 2016). The findings in this instance can be inconsistency and violation of expectancies by the organisation, when BI analyst unknowingly has to perform analysis on the data which by regulations requires privacy or has legal and financial expectations to it. Hence, the consistency in terms of the availability related mainly with sensitivity and from the perspective of legal and financial requirements are being practised by analysts using data governance practices, such as, by initially identifying the sources of data, the interfaces and by looking at the legal requirements related with sensitivity are completed. After this process, the data storage and access are defined in order to ensure that when questioning the frame, the sensitivity, the availability and access to information are

sound in the business context. The can be very influential, if BI analyst were not required to access certain sensitive data for the analysis or if they were given the right data at first place.

"we also need to look at the governance of the data. So, let's say it would be sensitive data or for legal perspective or financial perspective, it's really important that we have the data governance on that, because maybe it's easy to set up from a technical point of view, but if we don't have the right mechanisms in place it doesn't help if we have built the best integration ever. So, we need to look at the whole aspect" (IKEA BI Analyst, 2018).

And,

"so we would go down the route of identifying those sources, the interfaces, look at the legal aspects; is it ok, is it sensitive; we need to follow certain procedures how to store it, how to provide access to certain people, and then we would" (IKEA BI Analyst, 2018).

4.1.5 Seeking and Preserving a Frame

When seeking and preserving frame, people perform explicit search to find information finding anchors (Klein et al, 2007). The finding indicates the same, as stated by the BI analyst:

"We posed a question to some analysts; "how you predict sales?". It was quite varied, the answers that we got back. When you base your starting point on last study, then you are already on wobbly ground, I think. Is it relevant that we took X amount last year as a base for my prediction for this year's sales? I mean, it's not maybe relevant for this case (IKEA BI Analyst, 2018).

The findings go further in line with the literature, when people explicitly seek new frames or the reason is because they were exposed to new data, they may also make no initial sense and in some instance since data points at new frame, hence existing frame can be replace with new and better ones (Klein et al, 2007). We findings indicate the same, as stated by the BI analysts,

"We need to make sure we have a better understanding of what the question is. Maybe that's the failure there, if we do have one. You get assumptions thrown at you that it's the "whether", is it this or that, but it's never like, "okay, prove that to me, then, show me the analysis and improve, what is the margin of error here? That's not always so usable. A lot of its historical when we've done it like this forever, so we we continue to do it like that. There are things that we need to change, some of these ways of working, I think" (IKEA BI Analyst, 2018).

Subsequently, the emphasis initially is of better understanding business question and not assumptions. This goes in line with the literature that the nature of sensemaking will differ based on the demands of given task and we find this to be relevant here as well (Klein et al, 2007). Also, another supporting point from the data frame theory is that sensemaking activities have different barriers to overcome and therefore in each situation has to be treated differently (Klein et al, 2007). In that way the BI analyst sheds light upon the data anchors, which will help guide the analyst in seeking the right questions or frame. In addition, some data elements may become relevant now and were not before for BI analyst, because of the disorientation of person (Klein et al, 2007). As is the case here and pointed out by the BI analyst, they want to improve the ways of working, by understanding and asking the right questions may lead them towards better data analysis. Moreover, when seeking frame, the preservation of it another aspect, by explain way data or conduct fixation error that was produced by inaccurate anchor before (Klein et al, 2007). The findings indicate these important areas as well, as stated by the BI analyst above, they even consider preserving the existing frame (concepts, idea, business value propositions) since they might not be usable in light of the newly acquired data as indicated in the statement 'what is the margin of error here?' That is not always usable.

4.1.6 Re-Framing a Frame and Comparing Frames

Reframing is about revising goals, establishing news anchors to sharpen distinctions identifying alternative frames of understanding or simultaneous testing to reach to higher level of understanding (Klein et al, 2007; Pontis and Blandford, 2016).

The findings go in line with the literature as stated by the BI analyst, their works involves a lot of experiment design and that also steers what data they need, so here as mentioned in literature, reframing of the problem is conducted sharpen distinctions get insights into solutions and problems they are facing. The experiments by BI analyst at IKEA involves different stages of experimental design, where feedback is collected using qualitative data as a to understand what works and what does not,

"Yeah, its experiment design, which also steers what data we need. You also see the different stages of the different solutions. Initially we usually find it's a lot about the qualitative data, if it's this concept of co-creation where you don't create a solution but you instead let other people create solutions together, which is a core component in design thinking for example. So in the early stages it's a lot about that; showing solutions to people getting their feedback, which is a lot about emotions and the qualitative side. And then further on you go, you can start trading solutions and then solve more into A/B testing and the quantitative data" (IKEA BI-Analyst, 2018)

The reframing as mentioned in the literature review may also allow comparing multiple frames when there is a requirement for it (Klein et al, 2007). Comparing frames allows having a plausible and sharp understanding of what is really going on (Klein et al, 2007; Pontis and Blandford, 2016). The findings indicate the same understanding by BI analyst but with some issues related to it, as stated below, since organizations are very silo driven, hence different functions create their own version of truth which creates challenges for BI analyst in terms of the availability of the frame from different department so that they may compare and identify multiple frames for the problem or situations in hand. In addition, the findings indicate that BI analyst would like to have a community approach towards data analytics. By sharing solutions (frames) that are built in other functions of the organization, for example, dashboards, visualization of report among other important reporting techniques for data analysis. In that way, we find BI analysts are taking an approach of comparing different frames (solutions) to find the most suitable ones,

"We're very silo Driven, we have different functions create their own version of the truth, as it were, and its part of the work we're doing. Now is to try to break down those silos and take a more community approach to data analytics. And actually, it doesn't really matter who builds, but just share it. So, if we have a good solution build somewhere, then share it. So, this is a little bit of what we're facing right now" (IKEA BI-Analyst, 2018)

Moreover, another interesting area is identified in the findings in relation to reframing and understanding, as stated below by the BI analyst. If an employee moves or leave the company and the reporting is conducted using an Excel program, the whole process and understanding of it needs reverser engineering, but the BI analyst finds this to be a problematic and challenging issue. And also goes in line with literature, problem is directly related with the reframing when data anchors are to be understood and adjusted by the analyst to make sense out of what is actually happening and hence very crucial for them (Klein et al, 2007).

"It's very Excel driven, as I said to you, so if somebody has some recurring reporting that they're doing, and they change jobs, then it's somebody else's job to sort of reverse engineer that excel file and look at all the formulas and everything and try to understand it. It's not a reproducible product. Again, it's part of our journey, deeper into analytics. But today, that's where we are" (IKEA BI-Analyst, 2018).

4.2 CDON Case Context

The same definitions of a frame as explained in the IKEA case context is applied here (Frame - Definition). Also, here we have added the identified tasks, but this time from our interviewees in the second case analysis.

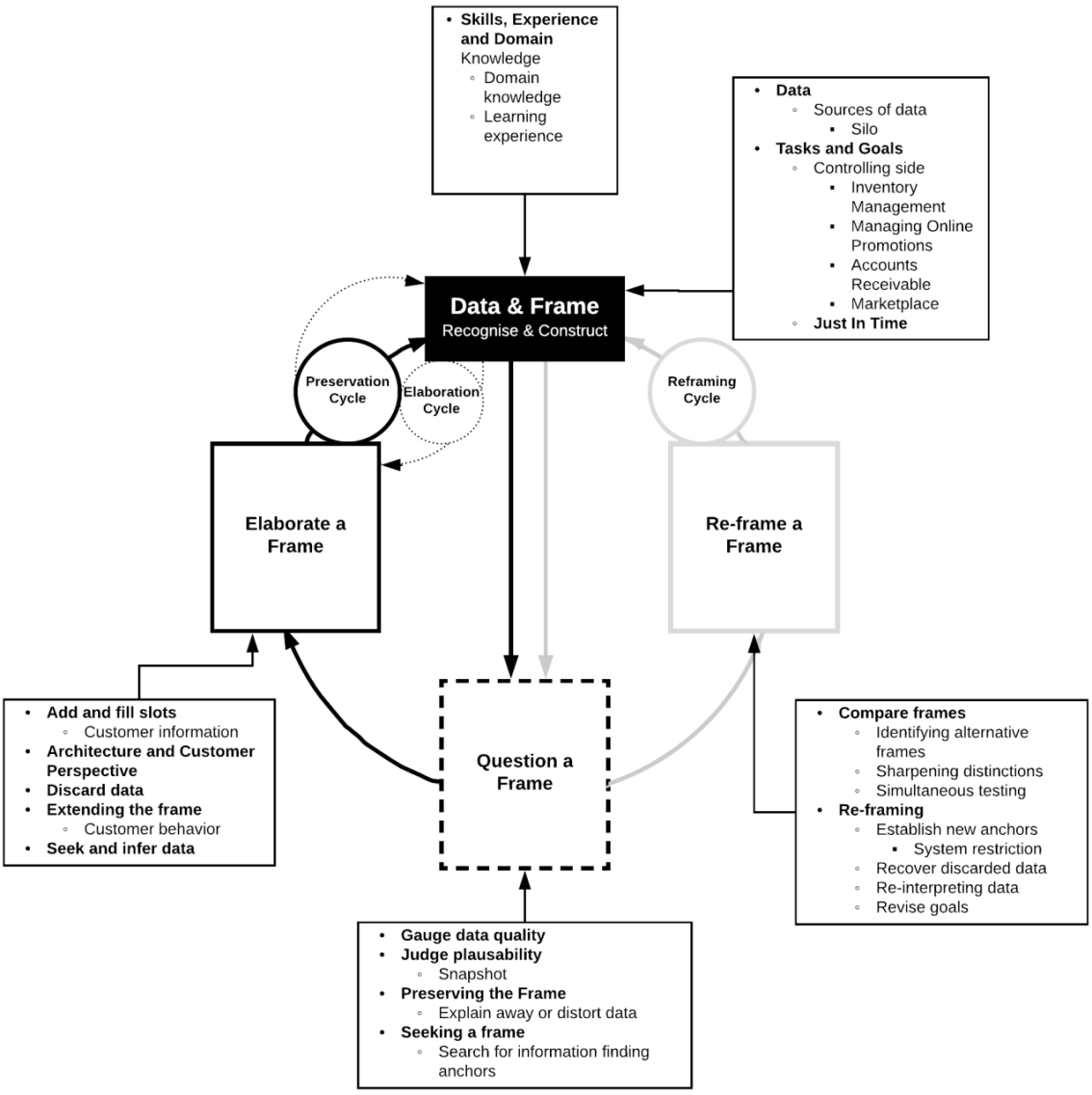


Figure 4 Data/Frame Model of BI Context-CDON

The finding and analysis presented are from business controlling department at CDON AB, Sweden. Additionally, the chapter follows structure that emerged from the data while coding process was conducted, available at, Appendix 8, which then is analysed using the Data/Frame Theory of sensemaking in the BI context. The interviews transcript data for the BI Business Controlling team is also available at, Appendix 6 and 7.

4.2.1 The role of Skills, Previous Experience and Knowledge

The initial findings indicate, that CDON business controlling domain is accustomed and use business intelligence and analytics and tools in their respective department within the organization, as stated by the BI analyst,

"QlikView can be a very good tool if you have like 10,000 customers buying a voucher code, you have a huge data and then we can scale it down with these applications. [Shows QlikView on screen] We can see if it's a voucher" (BI Analyst. CDON, 2018),

First of all these findings are in line with BI&A literature as mentioned earlier in the respective chapter, businesses use BI&A in the are making important on-time decisions, predictive analysis and reporting by producing dashboard, stories or maps (Watson and Wixom, 2007). In addition, the findings as mentioned above also indicate the use of BI tools by the analyst. Indicating BI analyst are well prepared for using more advance BI-tools, such as QlikView and Google Analytics for business questions data analysis.

Furthermore, as stated by the BI analyst, the BI tools help them to analyse large amount of customer data by scaling it down to solve business challenges. These findings go in line with the literature on business intelligence, which highlights the value of BI&A residing in making beneficial decisions from data (Watson and Wixom, 2007). Meaning, when BI&A tools are used for the benefit of organization, it will improve the processing, lower strain, increase productivity and allow for better adoption of business intelligence and analytics in the organization,

"we need to maybe use it in Excel, but of course the first steps decrease it very good. I mean, especially for us, with so many transactions and orders. That was not the case for example in our previous companies. We didn't have that many customers and orders in this company. Here QlikView tool this a very good at scaling down the data processing" (BI Analyst, CDON, 2018).

However, besides using the BI tool, the decisions making relies upon sense making skills as well as mentioned earlier in the literature review, it is an informational task to create an understanding of a concept, knowledge area, situation or a problem at hand and to solve ill structured issues by obtaining situational awareness or by exchanging knowledge with others (Pontis and Blandford, 2016; Zhang and Soergel, 2014; Pirolli and Russell, 2011).

We find the same in the findings from BI-analyst, as stated below, for the analyst it also about learning new things and processes and finding new ways to work with tasks at hand using previous knowledge and experience:

"The step over to controlling, for example, for me now it's several months of learning that you get one thing to do, when you try that and then they add new stuff. And sometimes it's new processes. And then you will have to find your own way based on what you already know. But I would say that we are we are well prepared on the at least basic stuffs, and then when there is new things and maybe it's a little bit more ad-hoc" (BI Analyst. CDON, 2018)

Furthermore, the BI analyst applies his previous knowledge of the domain in his work area. This goes in line with the literature on skills and domain knowledge which indicates that a person can feel deficiency in the ability to understand, grasp or grip the events or situations and that is when sensemaking comes in to action by responding to the situations, events or task/goals using skills, previous experience and knowledge (Weick, 1995; Klein et al, 2007).

Also, the findings above indicate, once the BI-Analysts are acquainted with the ways of working, they start to expand to apply new ideas and concepts while working with data information. In correspondence with the literature review, the sensemaking activities are not only triggered by the detection of anomalies but are also used to extend ones existing understanding of what is going on (Klein et al, 2007; Yi et al, 2008).

Similarly, the findings from BI-Analyst points out the same; once BI analyst acknowledges they have enough understanding of business challenges, situations or events, for example, as point out by BI analyst, they have a second role at accounts receivable in making sure and confirming that everything which was booked on the accounts, as per current information, is corrected and verified again, and then also building upon the process and improving the sensemaking when faced with large amount of documents in order to find the best possible way of doing it next time..

"But then it's like I said, I have a good learning experience in the beginning here where they taught me how they do it. And then you do it in that way until you feel like; okay, now I understand this good enough that I can start implementing my own ideas. So, for example, in accounts receivable it's usually making sure that everything that we kept on the bank is booked, but we get a lot of payments from so many ways and we have so many different foundations it's not always easy to make sure that it's completely correct. Sometimes it's alright that if there is a small difference, and how we make sure that everything is alright, that process when you started to understand it then you could start improving it, so it works better for me. Because you take over a lot of documents from the person before and maybe in their world this was the best way to do it, and then invites another way of the things" (BI Analyst. CDON, 2018).

4.2.1.1 Summarizing the role of skills and previous knowledge

The role of skills in BI-Tool such as, QlikView and Google Analytics is visible in the domain of Business Controlling at CDON AB. Additionally, the use of previous experiences and knowledge of domain is also present and helping BI analyst in the process of generating insight through sensemaking.

In addition, the skills, previous experiences and domain knowledge are further present with additional findings and analysis conducted using data frame theory of sensemaking (Klein et al, 2007) in the next few chapters. Also, the interviewees were guided by the theoretical framework in semi-structured way, using data frame theory of sensemaking. Therefore, the study presents statement gathered from coding process conducted using Nvivo.

4.2.2 Forms of Sense Making

4.2.2.1 Connecting Data and Frame

4.2.2.1.1 Tasks and Goals

Although sensemaking as described in literature does not have a starting point, it can be triggered depending on the requirements; for example, a trigger can be initiated by the data that require further elaboration or can also be as change in a frame (dashboards, reports etc) or maybe a frame will need a data input (Klein et al, 2007).

In line with the literature above, the findings from BI analyst as stated below, indicate when BI analyst use data for tasks, events or situations in hand, they start with an initial requirement set by the organization on to the BI-Analyst in relation to normal routines around their online marketplace on internet:

"Since we are a marketplace, a lot of the merchandisers are connected. We get commission. We brand their products on our site. So if you're going to furniture, for example, we are not distributing furniture's, it's not the company. I can show you if you go to the website, you can see in the article there is a line saying if it's a CDON product or merchandise product" (BI Analyst. CDON, 2018).

First, the findings mentioned previously goes in line with the literature mainly highlighting the role experts (Business Controlling) focusing upon the functional understanding to have a practical approach towards their daily tasks (Klein et al, 2007).

Secondly, in addition to above findings also indicates when BI analyst works with branding client products on their shopping platform, this can be seen in line with the literature as a conscious process of connecting data and frame, however depending on the available data (Pontis and Blandford, 2016).

Third, we can also connect the activity mentioned above by BI analyst, in line with literature, pointing out that when people fit data into frames (objectives, task, goals) and frame to allow direct people towards data in return, whichever comes first (Pontis and Blandford, 2016; (Klein et al, 2007). Hence, the role of data and frame becomes visible and needed when generating insights.

Furthermore, findings also point out a deliberate and conscious actions of a BI analyst, as stated below:

"Another part is to make sure that, for example, when we sell something usually there are agreements with the companies that sell the items. So we can have a lower price because they help us with a part in it for example. So, we need to follow-up on that we actually get in everything we want" (BI Analyst, CDON, 2018).

These findings a similar pattern discussed earlier and are in line with the literature, when BI analyst manage client agreements, this is seen as a functional everyday task activity rather than an abstract one (Klein et al, 2007). The work of BI analysts in the business controlling domain requires a follow-up on routines tasks by keeping themselves updated with agreements and prices of few thousand products.

In addition, the findings also indicate the motivation of an expert having a richer repertoire, using previously and already build routine frames (objective) of the functions, which than

guides them through daily challenges related with their tasks, goal or events for which they are aware and prepared:

"It's more checking so that we don't have any leaks that we should not have. so, for example if in our warehouse if there is something, that we're taking something out of the warehouse that the customer have not bought then of course then we need to know okay, why did you take this out? Was it because it was destroyed in handling, or is it going to some marketing campaign, or why did we take this out? So, we are just making sure that we should not have those kind of leaks, that's one part" (BI Analyst. CDON, 2018).

The tasks and objectives mentioned in the previous statement by the BI analyst are related to data analysis of inventory supplies by finding the unexplained inventory waste or leaks during the product storages and handling in warehouse and also during product marketing campaign was conducted.

In line with the literature, the role of sensemaking takes the form of an established frame of understanding, and then feeding or searching data for it commences (Klein et al, 2007), where the data represents the signs of events and the frames (leaks, waste, marketing campaign) represents the explanatory frames of the account for the data (Klein et al, 2007).

Moreover, the findings also indicate that BI analyst have additional responsibilities towards some financial tasks, such as accounts receivable, as stated below by the BI analyst:

"On that accounts receivable side it's; okay, we have this much money on the bank, how much did we expect? And then of course see if there is any difference between these and we of course check it out. But usually it's used… okay we expect 100, we got 100, and then we book it so that's pretty straightforward on the accounts receivable side" (BI Analyst. CDON, 2018).

The routine task and frame of understanding is understood as a straightforward task of analysing data with respects to how much money the BI analyst expects and how much they have in the sales report. These findings are in line with the literature, pointing out the frame of understanding, such as accounts receivable changes as per BI analyst expectations as frame and data feeding in to it, seen as an interplay between data and frames, where frame guide which data to find (Klein et al, 2007).

Also, as mentioned in the literature earlier sensemaking goes beyond one's current and established understanding or knowledge of a frame (Klein et al, 2007). Such as, by creating just-in-time (JIT) models, or frame constructed at the time of need, people can extend their understanding without relying on the established frames (Klein et al, 2007). The findings indicate the same, as stated by the BI analyst,

"And of course, it is like this in a company when we are growing all the time and we're putting new things in like the marketplace parts. And now we have launched a business to business site last month. We launched it and then afterwards we were "how do we handle the data?" (BI Analyst. CDON, 2018),

The essence in the findings points out, when CDON grew from B2C (business to customer) to B2B (business to business) by launching new website, the analyst faced issues with a particular question: 'how we handle the data?' This event and situation requires just-in-time models to carter to business needs and objectives but also for the BI analyst in this is new and unexplored situation. Similarly, as in line with the literature, the data plays the role of an anchor which will help the BI analyst to create solution and frame of understanding using business intelligence and analytics to make sense out of data and generate insights.

The findings also indicate another example of just-in-time models when connecting data and frame (Klein et al, 2007), when quick decisions are needed based on the available data, as stated by the BI analyst:

"The average we gain like 10% on this product. So, it's a good margin for us so we don't need to take the risk either, getting it in stock and handling it" (BI Analyst. CDON, 2018),

The previous findings is line with the literature, in terms of the skills, previous experience and knowledge is needed here when making just in time models, for example, as mentioned in the above statement by BI analyst, if a "good margin" is found on products by the BI analyst when analysing the data, the company can avail the opportunity to act upon it for themselves.

Also, another example of just-in-time mental is that of an event initiated based on the requirement, as stated below by the BI analyst, if customers are "CDON Plus Customers". Then the frame of understanding when analysing and generating insight from data indicates free freight delivery and return, this helps BI analyst to do on-time data analysis and in return it helps organization to take on-time decisions to lower order processing costs among many others benefits in the process:

"If it's a CDON Plus customer which is the customer who has Signed on to us paying like 1,50 SEK one-time fee, and then he gets free freight cost. Here you see membership, if you pay 1,99 SEK, you get free freight and some kind of return when you purchase. So you can use this purchasing" (BI Analyst. CDON, 2018).

4.2.2.1.2 Data Input

Once the objective, tasks, goal and other related issues such as just-in-time frames are defined, then they commence the process of connecting data with frames and frames with data as a next process (Klein et al, 2007). The data represents the interpreted signs of events and frames are used to explain the data (Klein et al, 2007).

In line with the literature, the findings indicate that while BI analyst work with business the task and goals by using BI tools like QlikView to find information, website traffic data, as the following stated by the BI analyst:

"[Shows on QlikView]. Here we can see the traffic in April. Here are some data, and then you saw in the marketing app there is some other data. We have so many sources also. We don't talk like one system where we gather all from. Maybe we do sum up everything. And of course, it is like this in a company when we are growing all the time and we're putting new things in like the marketplace parts" (BI Analyst. CDON, 2018).

By showing to us, the BI analyst illustrated, how they combine different data-sets for different business questions and put great emphasizing upon the different systems that are being used to gather data. The BI analyst also pointed out that, the organization is growing rapidly, and they must put new products in the marketplace (CDON, web platform). The findings here are in line with literature we discussed earlier in connection with data input.

Also, in relation to the data-sets from different systems is clarified further as silos, as pointed out by the BI analyst:

"We are still a little bit restricted based on what systems we report everything in. so it needs to be able to push into this system. So you can't go completely out of the box. I can't really come up with an idea where completely changed something, but it happens all the time that we started picking the data from a new source. I get the feeling that we are working more and more towards getting everything into one source and trying to get work less and less in other systems" (BI Analyst. CDON, 2018).

In this way they are working to push data sources towards one source to combine to get benefits on productivity in terms of less work and less burden in other systems. This aspect is also directly in line with literature discussed earlier, as the companies want to lower cost and increase the speed of processing.

4.2.2.1.3 Summarizing Connecting Data and Frame Analysis

For BI the analysts at CDON, the process of connecting data and frame starts with functional understanding, their daily routines and tasks where they analysed data for the existing and established frames, both in business controlling and accounts receivable functions. However, the findings also indicated the use of just-in-time models, and by carrying data analysis, the BI analyst were able to respond to a specific customer segment to offer promotions, by filtering and connecting the data with events and just-in-time models.

The next chapter present the elaboration of the frame, when the need arises to seek data, infer data and extend the frame by adding and filling empty slots.

4.2.3 Elaborating a Frame

4.2.3.1 Add and Fill Slots

Elaboration of frame is needed when people would like to extend the current understanding of frame by finding and adding more or relevant information to fill the empty slots (Klein et al, 2007; Pontis and Blandford, 2016).

This is in line with literature mentioned, as stated by the BI analyst:

"These special things like postal code or name or age, so you cannot go into detail see specifically if it's this customer, or "I love this". You can see female or male, and which language. You can pretty much scale it down to anything you want, how customers purchased" (BI Analyst. CDON, 2018).

The findings indicate, BI analyst increase their understanding of current frame with new business questions, for example, "how customers purchased?". And answers these types of question through scaling down in data and adding more relevant and update information by filling the empty slots that needs further information, such as, in the given statement below analysing customer information.

"You can see the emails and customer number and everything" (BI Analyst. CDON, 2018).

The above findings also indicate the use use of BI tools skills and most importantly the role of previous experience and domain knowledge, since the BI analyst mainly work with business controlling, associated with business operations. The question asked within the domain are relevant and domain specific. The findings go in line with literature discussed in relation to, when mental activities are initiated, such as, sensemaking the clarification and removal of ambiguity is necessary (Namvar et al, 2018 cited in Weick et al, 2008; Russell et al, 1993; Brown et al, 2008; Dervin, 1998).

In doing so, the BI analyst is also making sure that the quality of sensemaking is relevant because it affects the quality of knowledge created and decision taken on that knowledge will follow (Namvar et al, 2018 cited in Weick et al, 2008; Russell et al, 1993; Brown et al, 2008; Dervin, 1998).

Another, interesting aspect indicated in the findings here, when elaborating the frame to fit goal and objectives, the BI analyst stated, "I love this, you can see female or male, and which language. You can pretty much scale it down". The findings go in line the literature, when data act as candidate influencers than people can have a better understanding (Klein et al, 2007 cited in Medin et al, 1997 and Wisniewski et al, 1994). Also, as indicated earlier in the findings, BI analyst working at business controlling performs tasks in a routine manner. In line with literature, the elaboration process continues until there meaning of data is somewhat tangible and cohesive (Kolko, 2010).

The elaboration of frame is further explored with in depth finding and analysis, in following sub chapters.

4.2.3.2 Discarding Data

During the elaboration process of frame, data can also be discard, if the data elements are not the representation of reality to some extent, if not perfect and, or if they are not relevant in the given situation in hand (Klein et al, 2007 cited in Medin et al, 1997 and Wisniewski et al, 1994).

In line with the literature as mentioned, the findings indicate, as stated by the BI analyst,

> *"I would say that sometimes we have too much information. When they started a process, it was usually like; okay, we have all this information, let's just put everything in. then of course maybe not all of it it's important for the things that I do. (BI Analyst. CDON, 2018),*

As indicated sometimes too much unrelated information is gathered, which than is discarded by the BI analyst, since there is no use of the data elements in the given problem and hence can prolong the process of sensemaking that is mostly needed with the relevant data elements.

4.2.3.3 Extending the Frame by Adding Relevant Data

Also, during the elaboration process, as discussed earlier and in line with the literature, frames can be extended by only fitting what is needed to fill the slots (Klein et al, 2007; Pontis and Blandford, 2016). The findings point out the same,

> *"Someone else sitting at the development department or purchasers that use, let's say, this column of information, but I'm only interested in the first three. So of course, then I don't really take any notice to the other information, it's the information that I will need" (BI Analyst. CDON, 2018),*

So, in this way the process of sensemaking is extended by the BI analyst to gain more benefits by adding the most relevant information to the frame (objective, goal) and the rest is ignored and maybe is used by another domain with CDON (development or purchasing).

4.2.3.4 Seek and Infer Data

Lastly, like the findings and analysis above, seeking and inferring data will continue as an elaboration of frame to find more benefits or more exploration opportunities, the process of sensemaking will be expanded further to seek and infer data (Klein et al, 2007; Pontis and Blandford, 2016). We find further clarification with regards to this specific point in our findings, as by the BI-Analyst, when promotions and vouchers were given out to customers than

the outcome of it is analysed by posing a question on how many customers have used the voucher, which one and how much is left,

"Cost with the voucher codes that were given out, then we need to analyse how the customers that use these codes, which ones have used it? how much they still have left? That can be a big process, and then of course you have all the data that you need to gather; when was it used, and I don't have to recalculate it, how much they have used of this" (BI Analyst. CDON, 2018).

The findings mentioned are also in line with further literature, when elaborating the frame people identify new strategies of identifying source of information and the type of information to be collected can be adopted (Pontis and Blandford, 2016). Similarly, in the statement above, the analyst points out the experimental approach towards information analysis. By conducting a promotional sales using, a voucher, this being an initial frame (objective). The analyst than performs data analysis to find out, if any business value is being created using this method.

4.2.4 Questioning a Frame

4.2.4.1 Data Quality and Relevance

While connecting data and frame or elaborating a frame, the frame itself can be questioned based on the data elements on which the frame anchors itself. Also, as mentioned in the literature review, questioning of the frame may arise, if unexpected or inconsistent data is observed (Klein et al, 2007; Pontis and Blandford, 2016). We find similar perspective, as stated below by the BI analyst,

"And also of course you have to validate your data, because we have a lot of data, you know. And maybe it's better to get the data from another source because that data have already filtered out this and this. So yeah, that might be a problem when it's new things to do. First, make sure that you get the data from the best source, because we can usually data from a lot of sources" (BI Analyst. CDON, 2018).

Also, in another example like what we analysed and discussed above, the data at accounts receivable must be kept with minimal error or almost none. This seems to be crucial practice for analysts as it may interfere with their initial frame of understanding when dealing with tasks such as, accounts receivable.

"So for example, in accounts receivable it's usually making sure that everything that we kept on the bank is booked, but we get a lot of payments from so many different ways and we have so many different foundations it's not always easy to make sure that it's completely correct. Sometimes it's alright that if there is a small differencet," (BI Analyst. CDON, 2018).

4.2.4.2 Judging Plausibility

When questioning a frame, the plausibility of it can be analysed from by looking at how data was used. Since frames are dependent upon data and how fast and accurately the data is analysed, given the huge amount of data as mentioned earlier, that is 95% of unstructured data in the world and hence becomes challenging for organization (Gandomi and Haider, 2015).

The study finding point out the same, as stated by the BI-Analyst,

> *"We can filter the data for example if we have all the data for 100 000 customer orders we can easily find that specific information. So QlikView is of course good to use when we need to scale it down" (BI Analyst. CDON, 2018).*

The plausibility here is related with the use BI tools and sensemaking mental activities of a BI analyst, given the large amounts of data coming from one hundred thousand customers, as in line with the literature, when surprise arise, or inconsistent data is observed, people may adjust frame on which they have initially relied (Klein et al, 2007). Meaning, the changing and expanding nature of this business requires from the BI analyst to constantly update and use new anchor. Hence, since frames are dependent upon the consistency and speed of data, as we can see in this case than plausibility is possible given the analyst uses relevant tools for the task. Also, if the analyst has background knowledge and skills, which can then support influential information indicator using BI-tools (Pontis and Blandford, 2016). which is clearly seen in the findings above.

4.2.4.3 Seeking and Preserving the Frame

Seeking a frame is initiated as an explicit search, as pointed out in the literature, when people are exposed to data they tend to make sense out of it, and build frame, concepts and sometimes when the existing frame is in question, they look to replace the frame with another one (Klein et al, 2007). The process includes analogies, searching for more data to find anchors for constructing new frames or replacing them (Klein et al, 2007).

The study findings are in line with the literature, as stated by the BI-Analyst,

> *"Yeah, we always try… maybe you use the same way if you know it's a good way of course. But since we are a team we always try together to brainstorm together "okay, how can we do with this one if it's a better solution, how can we find it". But of course, sometimes if you know it's an easy way and you have a tight schedule, you go with that one. So maybe you're not always thinking out of the box" (BI Analyst. CDON, 2018).*

As mentioned by the BI analyst, they always try to use the same way when working with BI&A. But in many instances also considers seeking frames together with team members to build better solutions and looks for answer to questions like, "If it is a better solution, how can we find it?" However, the analyst points out that, it is not always that they have think outside the box, meaning that the processes are the same when analysing data, with same routines and they don't focus a lot on new solutions.

4.2.4.4 Re-Framing and Comparing Frames

Reframing and reformulating as mentioned in literature is an important practice, usually initiated by revising and replacing frames by establishing new anchors, recovering discarded data, re-interpreting data or revising goals and tasks (Klein et al, 2007; Pontis and Blandford, 2016). We find similar and interesting practices by analyst, as stated by the BI analyst, for analyst the rules already set when solving issues and problem, they have been doing it for many years,

"The things or the rules are already set, so there is a way of doing it. Then of course maybe you can come in and think "why are we not doing it this way", then it is like "ah, because we have done it 10 years", and no one have time to question it" (BI Analyst. CDON, 2018)

However, upon further inquiry the analyst the analyst pointed, as stated below, it's easier to find information they want to work with, but most of the times due to the amount of data, and data residing in bigger categories, finding the lowest level details about transactions is challenging and relating it back to the frame of understanding is harder, so the question analyst is asking, how to find out the exact numbers?

"When we compared the booking at the end of month it's not negative margin, so in some cases it can be easy to find it, but of course some cases that can be very difficult when you have, like we saw before, you only look at the big topics of the channels of your countries, you don't really see the data at the lowest level. When you have so many transactions you don't catch everything, so that's maybe the question for us – to find out the exact numbers" (BI Analyst. CDON, 2018).

Additionally, in line with the literature, frame can be compared to find out what is really going on and people might use multiple frames (understandings) to sharpen their understanding or in some case some multiple frame are part of a larger category and upon activation of one category will trigger and activate the rest of the frames (Klein et al, 2007 cited in Feltovich et al, 1984).

We also found similar activity by the analyst, when they started comparing multiple frames, as stated by the BI analyst,

"It's comparing the reasonable data to see if it's accurate. It's sometimes difficult to see if the quality is good. Of course, in QlikView you always have to question yourself if the numbers are correct. I remember a couple of weeks ago for example for digital games, you know these when you purchase a code for a piece for a game or something, and we had a problem with the purchase prices in the system, so we got a negative margin. But that's only the numbers in the report, because it didn't make a change in the ARP system, which we didn't' catch in QlikView" (BI Analyst. CDON, 2018);

And,

"If it's routine stuff then usually you have somewhere in your mind like: is this amount that I get reasonable? If you want a hundred and you get a thousand, then something might be wrong here, and then you start looking it through. So in the routine it's just what you have in your back of your head. Sometimes we also have information from two different sources that you match together, and if there's a difference then something is wrong. So then you find it out that way" (BI Analyst. CDON, 2018).

While using different reports and frame of understanding the analyst can pinpoint the problem related with the purchase price of digital games codes, which are sold online. The problem started when margin were negative and wrong numbers in QlikView were reported.

Meaning that the data input was incorrect, hence the analyst considered looking at different system build for other purpose and their respective data sources, by comparing those frames and unique data sources, which were not the same as in QlikView, the analyst was able to pinpoint exactly what was going on with those negative margins.

4.3 Cross-Case Analysis, Similarities and Differences

The chapter presents similarities and difference through comparison between BI analyst working in BI Innovation domain at IKEA AB and BI Analysts working in Business Controlling domain at CDON AB in the BI context.

The main purpose is to further strengthen the analysis we set out to begin to understand, how analyst generate insight from data using BI tools. Also, the data-frame-theory of sensemaking by Klein et al (2007) was used to guide semi-structured interviews to record BI analyst original meaning of how insights are generated from data.

To explain the findings gathered from both individual case studies in terms, what is similar or different. The method adopted is cross case analysis (Merriam, 2009; Yin, 2014). Which will help this study to present the important findings from two slightly different domains and to be used in the discussion part latter to answer the questions we set out to begin. The emphasis is not to compare and select which case is the best in BI&A, but to bring to surface the capabilities and important insights needed to generate insight from data, from both case in a unified way. Hence, here now the study only present similarities and differences and followed by discussion and implication in next chapter.

4.3.1 Connecting Data and Frames

In line with the literature, when connecting data and frame it on the data, task, goals and repertoire of the person or organization (Klein et al, 2007). In these two case's the business intelligence analyst main task mainly resided in the area of solving business questions or context, experiments in the area of customers interaction, community approach to building and sharing solutions for IKEA other department (HR, finance, supply chain); whereas, when compared to CDON the focus is mainly on the operational side of business, using BI&A for branding clients products, maintaining customer agreements, monitoring and analysis supply chain issues and responding to just-in-time data analytics.

Table 1 Cross Case Matrix, Connecting Data and Frame IKEA and CDON

	Connecting Data and Frame - Similarities and Differences in BI-Context		
Case	**Tasks and Goals**	**Data Input**	**Skills & BI Tools**
IKEA	Reproducibility and Reusability improve what data we put in which context, clear business questions/problem, increase customer integration/meeting, experimental approach, create solutions, Digital Innovation around Data, Community approach to data analytics, Sharing Solutions (Create report, dashboards etc.).	Transactional data, Understanding Internal data landscape, Silo Driven, Right data and Consistency, Enterprise data warehouse robustness.	Modern Analytical Workflow, Exploratory Analysis, Business and IT domain Knowledge, Technical Knowledge (Programming and Coding), Previous knowledge, Richer Mental Model (experienced), Plausible Awareness, BI Tool skills in Cognos, QlikView and machine learning in Azure or in AWS, also Neo4j for graph databases
CDON	Branding Client Products, maintain customer agreements, analyzing inventory, Backing Marketing Campaign on operational side, Operational issues (accounts receivable and supply monitoring), Just-in-Time Models (Frames)	Customer Traffic, sourcing data from different systems (Finance, Supply Chain etc.), Silo driven but would like to move towards on system	QlikView and Google Analytics, Domain Knowledge (Controlling, Accounting finance and Supply Chain), Analytical thinking (implementing own ideas),

In both cases the use, the use of sensemaking process is seen as deliberate activity and where reasoning is employed using a conscious activity (Pontis and Blandford, 2016; Klein et al, 2007), for example, in IKEA case, the use of modern analytical workflow, exploratory analysis, application of mental richer models is present. Whereas, in CDON case the similarity is in the analytical thinking process by BI-analyst applying new ideas and concepts.

In addition, some BI tool is similar, for example, IKEA uses Cognos and QliKView, whereas, CDON also uses QlikView along with Google Analytics. The difference here is the IKEA BI analyst relies also upon auto recognition of patterns using machine learning in Azure and

AWS along with Neo4j for graph databases. In doing so, the approach adopted by IKEA allows reasoning that are influenced by unconscious processes using automatic recognition of frames and set of events based on the patterns matching process (Pontis and Blandford, 2016; Klein et al, 2007). Whereas, CDON consider QlikView and Google Analytics as BI tool for analysing data in their business controlling domain.

Additionally, both IKEA and CDON BI analyst understand the source of data and its complications, for example, in the findings it is indicated that understanding the internal data landscape (Silos) are as important for IKEA as much as for CDON. Since, the role of data element constitutes parts the together will help the analyst to makeup the frames (Kolko, 2010). Hence, the silo driven approach limits or stresses the BI analyst sensemaking processes, since the excepted requirements from BI analyst also on the consistency and just-in-time models and responding to either BI Innovation (IKEA) or operations and business controlling at CDON.

4.3.2 Elaborating the Frame

Elaboration of frame is conducted when there is a need to seek further data or extension of frames by filling empty data slots when new surprise or anomalies emerge (Klein et al, 2007; Pontis and Blandford, 2016). The elaboration of frame as mentioned by IKEA BI analyst, is based on pure logic, experience and the availability of integrated systems; whereas, CDON BI analyst is of view that by scaling down through data they are aiming at finding customers buying patterns to extend the frame of understanding. The sense making process in elaboration continues if ones find unexplained key data element/components of a frame (Klein, et al, 2007).

Table 2 Cross Case Matrix, Elaborating a Frame IKEA and CDON

	Elaborating a Frame-Similarities and Differences in BI-Context		
Case	**Add and Fill Slots (Data)**	**Discarding Data**	**Seeking and Infer Data**
IKEA	Adding data based on pure logic and experience, data integration using modern technology to ensure sustainability,	Due to cost, due to processing, better storage optimization, temporarily discard data and use as per use case	
CDON	Scaling down data, finding customer buying and behavior	Too much information, ignoring irrelevant data on database,	Analysing recent promotions,

Furthermore, some similarities are also found in both cases when elaborating a frame, this is when discard data and continue to add more data until the frame has a clear picture. For ex-

ample, IKEA BI analyst discards data either completely due to cost, processing and storage optimization, during experiments or temporarily as per their use case requirements. Whereas, the CDON BI analyst only considers ignoring data that might be useful for someone else in the organization and thus relies more on data residing in common systems. In that way the similarities consist of mainly around the central theme, by adding and filling data slots using previous knowledge and skills to find anchors that may serve candidate influencer (Klein et al, 2007; Pontis and Blandford, 2016).

4.3.3 Questioning a Frame

Questioning the frames arises due to fundamental surprise (Lanir, 1991; Cook et al, 2007; Klein et al, 2007). For example, when new data will not fit, as in the case of IKEA, when customer do not update their profile data, such as address or when the BI analyst are experimenting with BI-innovation (making reports, dashboards etc). Whereas, in the case of BI analyst at CDON case, they would like to consider good book keeping on accounts receivable otherwise it will interfere with their frame based on positive margins. In case of bad data input may lead to data being explained away by preserving the frame and going through the process of elaborating the frame as described earlier, to keep general structure of frame until better explanation are found (Cook et al, 2007). This approach is called seeking a frame and can be explained using, IKEA BI-analyst approach of seeking clear business questions and avoiding assumptions. Whereas, in CDON case better solutions and frame are brainstormed in a team but is not always thinking outside the box since the department is operations compared to BI-Innovation at IKEA. Moreover, what is different here is, frames used by IKEA experimental approach in BI-Innovation gets rejected, due to the increasing complexity becoming too unwieldy and hence frame is rejected for another one (Cook et al, 2007; Klein et al, 2007). The similarities and difference when questioning the frame in both case is also due to data relevance, such as, for IKEA, where unstructured data, doubtfulness in other systems, business understanding of data or data profiling issues are influencing the understanding of frame (business questions) of BI analyst. Similarity is found in CDON case, where validating the sources and data relevance to the task is important.

Table 3 Cross Case Matrix, Questioning a Frame IKEA and CDON

	Questioning a Frame-Similarities and Differences in BI-Context			
Case	**Data Quality**	**Data Relevance**	**Gauge Plausibility**	**Seek and Preserve Frame**
IKEA	Poor quality because customers do not update their data, data produced through experiments are not reliable.	Unstructured data issues (external sources), doubt in other systems, vocabulary or business understanding of the data is a big challenge, data profiling depending on the context,	Snapshot of data, frequency versus quality measures (sometimes frequency is important), good bookkeeping, data governance (sensitive data, legal perspective or financial perspective), Storage and providing access based on data governance policy,	Seeking better understanding of what the question is? Avoiding assumptions based on last study,
CDON	Good book keeping on Accounts receivable,	Validating source and data relevance,	Filtrering data using QlikView,	Using existing frames, brainstorming with team, but not always thinking out of the box

Except when a person finds an important anchor that is credible evidence or revised frame, it is called a frame-breaker (Cook et al, 2007; Klein et al, 2007). In that case a frame can be replaced for another frame (Cook et al, 2007; Klein et al, 2007). In both cases we find similar understanding by BI analysts, for example, IKEA approaches frame-breaker or revising frames through taking data snapshot by freezing and isolating the data to find plausible frames, since data are frame anchors, including that they facilitate good book-keeping and most importantly and interestingly the data governance policy towards data allows them to isolate sensitive data related to legal or financial areas minimizes the chances of framing experiment, or business solutions that are not beneficial for the organization, instead could be devastating and dangerous if these measures are not taken. Whereas, the frame breakers for CDON are generated through filtering process and scaling down the data that are evidences.

4.3.4 Re-Framing and Comparing Frames

Sensemaking allows to shift one's understanding of situations or events, when a person spots early signs of problems or initiatives to find a better or more reliable account (Cook et al, 2007). This require from a person to do to accumulate inconsistent or contrary evidences but also to replace frames to make way for searching finding cues or new frames (Klein et al, 2007). In line with the same theory, we find both case to have the view point given that important elements are fulfilled, for example, IKEA BI-analyst uses mainly experimental approach which steers them to find new anchors and this is made possible by showing solutions to people to get feedback, by revising goals at different stages of different solutions, adopting solutions (frames) from other departments and focus open reverse engineering the existing frames. Whereas, CDON BI-analyst approach to reframing is limited due to the nature of their domain, primarily focused on routines, as rules are set they may add and fill new slot by elaborating the existing frame but re-framing is limited. Additionally, for CDON BI-analyst while maintaining the existing frame of understanding, re-interpretation of data is conducted to fit data to frames using alternative frames and their data elements to match and verify.

Table 4 Cross Case Matrix, Re-Framing and Compare a Frame IKEA and CDON

	Re-Framing and Compare Frame - Similarities and Differences in BI-Context		
Case	**Establishing New Anchors**	**Re-Interpret/Recover Data, Revising Goals**	**Identify Alternative Frames**
IKEA	Experiment design, which also steers what data is need,	Different stages of the different solutions, Good solution build somewhere and then share it, Reverse engineer frames (Excel Reports).	Showing solutions to people getting their feedback
CDON	Less focus on new anchors (rules are set), no one has time to question it,	Comparing booking data for margin issues, looking for exact numbers (data)	Finding data from different frames, matching two different sources to verify.

5 Discussion & Implications and Further Recommendations

The study that has been conducted in this thesis has helped us to find new gaps in existing literature that has not been addressed in an adequate manner. Other studies, such as that of Pontis and Blandford (2016), have discussed and tested the data/frame model of sensemaking in and of itself, sensemaking as its own entity (Weick, 2005), sensemaking in terms of Human-Computer Interaction (Pirolli and Russell, 2011), as well as how organizations unravel, how they can be made more resilient in light of sensemaking in terms of how we understand organizations in terms of how we think about intergroup mechanics, team building, temporary systems, as well as other factors (Weick, 1993). Our thesis, however, is concerned with implications in sensemaking theory that highlights how sensemaking in a BI-context is generating insight from data. Other inherent implications regarding sensemaking that we found will be discussed in this section point-by-point.

Reproducibility and reusability:

While the reports might be conflicting in terms of what data they present, and which is more accurate, thus inviting little trust in these documents, there is a need for adequate reporting for the sake of reproducibility, and by extension also reusability, which in turn can be solved with improving the ability and process of putting the right data into the right context. This is especially the case for unstructured data. What can be derived is that the right data and consistency is vital for this end, ultimately enabling the organization to make adequate business decisions based on reliable and accessible information. The implications here are that an adequate data governance would possibly enable BI-driven organizations to employ controls that allows for a more consistent and reliable selection mechanism for data, allowing BI-analysts to easier pick ut the right data for any given context. Furthermore, persistent technical knowledge, such as programming skills would help to relieve organizations of this issue since proper data analysis techniques can be employed. What the correct skills imply in practice, as well as how skills vs experience affects the overall work performance, however, can be a subject for further discussion. Skills must also be accompanied with a proper and modern analytical workflow in order process the data once it is acquired to produce initial frames, that could however be improved by closing the gap between business and IT personnel.

Clear business questions/problem:

This goes together with having to define clear problems or questions pertaining to the business. A lot of the business users have the same questions, so by employing an adequate analytical workflow and programing skills, it can allow the right answers to be in line with the business questions that are being asked. This also goes in line with the importance of not only having the right technical skills so that the modern information flow, such as having stored data on mobile phones or the internet, can be accounted for, but also the addition of closing the gap between the areas of business and IT. This is an area that we feel has the potential to greatly benefit insight generation granted that other researchers are willing to investigate this topic in light of sensemaking, since the thinking, as well as vocabulary, of the two schools of

thought can, as outlined by our interviewees, become a problem in mutual agreement and understanding, thus slowing down and possibly diminishing the insights generated in the organization.

Experimental approach:

An experimental approach is undertaken in order to break down a problem into parts, that are then worked with in order to find optimal solutions. This is then tested with people, with the help of several versions, to isolate the relevant elements and examine and decide upon an optimal output variable. High speeds of data are said to be needed, which follows large amounts of feedback that need to be analyzed in a timely manner. While the idea is an iteration process that functions as a prototyping stage in data analysis, this also creates large volumes of data at different stages of the different solutions, which is a way of re-framing and comparing frames. This again goes back to the requirement of proper and right technical skills that can align with a modern information flow for optimal speeds. Furthermore, this kind of experiment design also steers what kind of data that is needed, again calling for adequate data governance.

Community approach, sharing solutions / moving towards one system:

Another part of the problem regarding the current state of inadequate reporting is the silo driven approach to creating reports, that leads to the problem of several independent data presentations. More sharing of the data produced is a proposed solution from one of the interviewees, to facilitate a more open "community approach" to data analytics in order to better being able to agree on solutions, possibly as per a consensus-based mindset. Expert BI-skills also needs to be shared among other BI analysts and business personnel so that the knowledge gap can be closed, or at least narrowed. It can thus be said that it is not an issue of necessarily outputting less but more accurate reports, but rather being able to make better use of it with the help of better technical skills and a more functioning analytical workflow to reach for the right data due to the nature of unstructured data. Another of our interviewees suggested data lakes, which they are currently experimenting with. Another way of tackling this issue is centralization towards one system so that everything can be accessed from one place, which combined with the other outlined needs and factors outlined, could have a big impact. An optimal solution for the structuring of data so that it benefits sensemaking could be its own area of research, since there seems to be uncertainty as to how one would structure the data infrastructure in a favorable manner for insight generation.

Just-In-Time:

Problems can however be solved on the spot by applying a Just-In-Time mental model, which was the case in the second case study. It means that the BI analysts looking at the data are not constricted by the data, but rather are able and willing to take decisions on the fly when the opportunity arises to do so. This is what is called functional understanding, as explained in the theory section. It must be stated however, that another important reason to work towards getting all data into one centralized source is to enable the BI analysts to go more "out of the box", since they are currently restricted by the reporting systems that they use. The problem of the silo driven organization can thus also be said to be a hindrance for generating insight, and mental models, on the spot.

While IKEA focuses on experiment design as mentioned, CDON instead have set rules that they follow, meaning that their focus relatively little on conceiving new anchors. Comparison

between data for making sure that, for example, the average profit margins are adequate to not warrant risk taking. This way of thinking is a way for comparison of frames so that they can detect any potential inconsistencies in margin profits. This can thus also be a case of re-interpretation when needed, after having matched two or more sources to verify the trustworthiness of the data.

In other words, the BI-analysts use sensemaking for determining when and if, and to what extent, their functional understanding should guide them, thus utilizing Just-In-Time frame of mind to generate further insight. In cases where the rules are more stringent, a comparison between frames is used as a method for determination and intuition, thus creating insight in that way. The wider implications of this, however, could be further researched to determine how insight can be construed differently.

Pure Logic and Experience, Data Integration and Sustainability, Data Storage Cost and Processing, Data Storage Optimization through temporary storage

The discretion of the BI analyst is the enabler of any further insight creation. Even though the right technical skills are important, it is not the only factor in handling data. Use cases can play a big part when elaborating a frame for example, as new unforeseen events can happen at any time, such as cases where different price levels come into play depending on the situation, meaning the data can be picked and utilized as per use case. This goes together with the Just-In-Time mental model, as it is just as much about the right decisions as it is about the right technical skills. While technical skills take care of the sorting and common interpretation, as well as understanding of what data is right, experience is what enables the following steps of actual and adequate data selection that is discretionary in nature and that facilitates decision making regarding how, for example, to find relevant customer buying behavior and scale down the data as needed. Further organization-wide business knowledge could be improved by training programs. This demands that the business logic is consistent, however, to know what data is unnecessary in which contexts. Modern data integration aided by modern technology allows for reduction of costs, better storage optimizations and a more effective processing of the data.

Experience is an important factor in the generation of sensemaking that must accompany the underlying skillset. Experience enables BI-analysts to utilize the Just-In-Time mental model to acquire a degree of insight. To what degree skills and insight interplay and depend on each other considering however, is a subject that has not been elaborated upon in this thesis, which should give future researchers and ample opportunity to investigate, should they be curious about this.

Data Quality issues

Factors such as some customers not updating their contact details may affect the quality of the data, as well as the results of design experiments may not be reliable in a business environment, are thoughts that happen after the initial frames have been conceived. Since this is something that is something that is outside the control of the organization, we would like to argue that this situation makes a strong argument regarding the need for closing the gap between IT and business personnel. This is because technical skills are, as discussed, imperative to the objective of proper data analysis and handling. Therefore, a proper way of communicating the data findings to the business personnel to create business value is the next important step in generating insights through sensemaking. The proper business understanding is a challenge, according to the interviewees. This shows that insight generation is very much

dependent on the collective understanding of data. Granted that this mutual understanding can take place the plausibility is evident where snapshots of data are taken and can become an even more effective tool in data iteration. In the same way, other measurements such as frequency vs quality of data, data governance and book-keeping can all inherently become even better tools of communicating selection and testing of data, granted both the BI analysts and business personnel are all used to the same kind of business understanding and vocabulary, which in turn would also improve reproducibility and reusability.

The question is how to further deal with irrelevant and untrustworthy data so that insight will not be negatively affected. Control mechanism would probably need to be investigated for organizations to compensate for this inherent shortcoming in data collection and management. Having this said however, from what we have heard and learnt from our interviewees is that with the right skills, experiences, governance, decentralization of data, as well as closing the gap between IT and business professionals, this problem can, and is, mitigated to an extent. Again, this is something that could be another area of research, as there is a gap in the existing literature regarding the implications of these factors and variables.

6 Conclusion

The first part of the problem that was introduced pertained to the large amounts of data produced and collected, which is challenging to gather insight from due to silo keeping, limited access, data governance issues, challenges pertaining to data quality and sourcing, lack of adequate and comprehensive skill sets and experiences of IT professionals, data management interpretation of the data and overall slow and non-optimal workflow and information flow. The second part of the problem was that not much scientific research has been conducted regarding sensemaking and insight generation from data within a BI&A context.

The research question in this thesis has therefore been: How do analyst generate insights from data using business intelligence tools? To answer this, we utilized the data/frame model of sensemaking to see how BI&A analysts generate insights from sensemaking through their activities.

The framework shows four main cycles, each consisting of sub cycles that outline key mindsets and procedures of BI&A- analysts when they conduct their data related tasks. Each identified task has been mapped to these tasks so that we can see how each sensemaking activity is correlated, and how data insight is ultimately generated.

We have used our interviewee's responses, which we then coded to derive their insight-generation in various key activities. These are:

Clear business questions/problem: First the organization make sure that the understand what the question to whatever problem they may have to solve is, by way of clearing it up, and then getting the right data to solve their task and goals.

Experimental Approach: An experimental approach is taken by IKEA when the focus on the problem is not complete clear and need a degree of elaboration and iteration in order to come up with an adequate and working solution. In CDON however, they compare frames and match them to verify data due to their set rules.

Just-in-Time Models: Are used for when there is need and opportunity to go beyond current and set knowledge that may be limited. This is especially the case for CDON for when they do not know how to handle new data.

Data integration: Using modern technology allows for cost reductions, better storage optimizations and a more effective processing of the data, which ensures sustainability

Data Plausibility: Controlled and checked by utilizing snapshots of data to scale down the data, which is important in both CDON's and IKEA's case in order to answer specific questions and facilitate a smoother analysis process. Good book-keeping is important for both IKEA and CDON. The aforementioned sees it as a means to an end, while the latter however, and sees it more as a direct data quality control mechanism.

Data Governance: Both IKEA and CDON are aware of since they need to navigate the legal and financial aspect of data management in order to know how to store and provide access to

sensitive data. The data governance employed allows the organizations to isolate sensitive data that would have harming consequences, should they not be handled carefully.

Adequate Data quality: Results in reproducibility and reusability. This is an area that has been lacking but has been identified as an organizational need. This can be achieved with the adoption of a more modern analytical workflow, as opposed to the one they are using now, which needs the right data to be used and made sure it is consistent. The data quality at IKEA can poor due to, for example, those having hard time keeping customer information up to date, which is out of the BI-analysts control. Quality of data also depends on the context, however. According to CDON, the data quality can vary depending on the source, which is why comparison and matching of data is important to them.

A Community Approach: BI analysts to share solutions is something that IKEA aims for but does not have at present. Instead, both IKEA and CDON are Silo-driven in how they manage their data, so that makes it very important for them to be able to understand their respective internal data landscape.

Pure logic: is something that happens due to the need to be prepared for future potential cases. It is used to add data from intuition. Experience goes together with this process since an intuition-based understanding needs to be employed. Skills and experience also affect the ability to determine the frequency versus quality measures of data.

Insight generation and sensemaking is a subject that has been studied in the existing literature, but not in terms of BI&A and its role in an organization. In this thesis we have illustrated the importance and implications of insight from data, in hopes that more attention will be given in this area. Whether improvements need to be made in terms of sharing skills and experience or applying a strong data governance, we have given concrete outlines of what constitutes and provides insight generation in organization from two cases; one BI-innovation department and one BI-controlling department. This shows that while insight generation can differ in some respects depending on the context, there also lies many similarities in what constitute adequate sensemaking. For this reason, future managers should take heart and not see this thesis as a guide; the quality of the insight generation depends on the discretion of BI analysts and the methodologies the organization chooses to use. It is our hope that this area will be further looked into, more specifically individual insight generating activities and procedures.

Appendix 1, Interview Participant

Number	Interview profile	Company name	length (in mins)	Form
1. Appendix 2, IKEA Interview 1	BI - Innovation	IKEA AB, Sweden	19	Telephone
2. Appendix 3, IKEA Interview 2	BI - Innovation	IKEA AB, Sweden	17	Face-to-face
3. Appendix 4, IKEA Interview 3	BI - navigation	IKEA AB, Sweden	33	Telephone
4. Appendix 6, CDON Interview 1	Controlling	CDON AB, Sweden	29	Face-to-face
5. Appendix 7, CDON Interview 2	Controlling	CDON AB, Sweden	23	Face-to-face

Appendix 1, Interview Guide

Connecting Data with the Frame (Influencers and Indicators)

Tell us about your tasks or problem that you might face in your daily work?

How do you get to solve these tasks and what will be the initial process or situations that you might come across?

How are these tasks related to your domain?

Have you faced these issues, tasks or situations before?

How well do you think you are prepared for these types of tasks and situations?

What would you normally do once you have the initial understanding of the given task or situation?

Elaborating the Frame

How would you go about finding information data for the given task or situation?

Did you ever consider discarding information data? and why?

Did you consider adding new information data? and why?

What do you do with the information data, once it is collected?

Questioning the Frame

Did you ever re-consider the quality of the data that you selected previously for the given task?

Tell us about the source of the information data for your task was it credible or trustworthy? if not then, what did you do about it?

What about the relevance of information data, have you encountered issues with that during the task? Was it consistent with your task and understanding?

Re-Framing

Did you consider coming up with other solution (s) to the task or situation in Hand? And, what did you do about?

Appendix 2, IKEA Interview 1

Interviewer: It starts with the task "how do you go about analyzing data". So the questions are framed around a particular task or work or situation that you might come across. To start with that, I would like to ask you to tell us about your tasks or problems that you might face in your daily work, especially that is related with data. How do you go about that?

Interviewee: Ok, so I think in here, compared to many other areas, the innovation department we work a lot with an experimental approach. So that's our approach to the task in that sense unless we have every focus on problem, and then trying to create solutions for solving these problems, but instead of creating the solutions we design experiments. And that's one thing that separates what we are doing towards many other departments here. So when there is a problem we try to break down that problem into different parts and then try to see how we can design an experiment around this problem and making it as kind of like scientific as possible, so meaning that we have an input variable and an output variable. So if you want to do some kind of experiment; like adding a gamification element to online training course or something, if that will increase the engagement of the participants. Then we try to isolate the gamification element input variable and then firstly, how can we define the experiment around it. So it means that, we need to kind of create two different versions and randomly assign people to this experiment in order to see if the gamification variable is deciding anything on the output, meaning the engagement. So it's a classic way of how you design a scientific experiment, but we need to rework so much, rather than about trying to get it into that kind of business environment.

Interviewer: Of course. So the in domain around that you will work with this innovation. But what would be the role of data in your domain actually?

Interviewee: So when doing these things there are two different types; there qualitative and quantitative data. So we work a lot with methods like design thinking, which is very much focused on the qualitative side, how do you emphasize with your customers to really discover what are their feelings, and then it's a lot about showing something, recording how people react to it, and letting them use it and play around with it and see how to do it. So that's one side. Then it's quantitative side. We generate tons of data from our online activities. Our web department, they use a lot of A/B testing for, how do you really find a web page. Any kind of flow on the web page. It's a combination of both. We need to do both quantitative and qualitative data analysis to do decisions.

Interviewer: Okay, so once you have the understanding then you go about like, first you identify what is the problem what, which are you looking at, and then you go about try to solve that? It depends what kind of data you need, right?

Interviewee: Yeah, its experiment design, which also steers what data we need. You also see the different stages of the different solutions. Initially we usually find it's a lot about the qualitative data, if it's this concept of co-creation where you don't create a solution but you instead let other people create solutions together, which is a core component in design thinking for example. So in the early stages it's a lot about that; showing solutions to people getting their feedback, which is a lot about emotions and the qualitative side. And then further on you go, you can start trading solutions and then solve more into A/B testing and the quantitative data.

Interviewer: So you keep on adding data when it is needed; it depends which state you are in?

Interviewee: It depends on what kind of question you will need answerer to. There is no strict process of how to do this. It's more about looking at what are the unknowns that we need to answer.

Interviewer: Have you ever considered discarding information or data, like removing it for some reason, and why? Meaning, has it happened that you considered a set of data, for example, quantitative or qualitative, and then you realize later on that you might not need this for the problem?

Interviewee: No, I think it relates to two things, the quality of the data; at IKEA we have tons of customer data around the world but it's also very poor quality. If you look at customers' home addresses and so that it's updated quite frequently. We can't really keep that up to date since it requires the customers to actually update it. So there's a lot of quality issues. And then on the other side you have more of an accuracy of the data, so quite often you when you design experiments, experiments design is extremely difficult to do in a business environment. In a scientific environment it's easier, I would argue, because then you can control the experiments better. In the business environment there are often very many variables which you can't control. The data generated sometimes isn't accurate because the design of the experience was actually wrong.

Interviewer: Okay, so that means that, you know in the business environment things change quite frequently and then you have to adopt somehow, right?

Interviewee: Yeah, it's also more difficult, I would argue to, isolate the experiment because we don't want multiple input variables into an experience, you only want to have one which you can alter. But if you want to do something out in the real world with real customers there are so many different variables to take into account. Also there are certain rules and guidelines that we need to stick to when we do things since we are a company acting with private people.

Interviewer: All right, that's very interesting to hear. I think you have already mentioned the quality of the data that you've selected and that also means the source of data that you select, right? Maybe the credibility, the trustworthiness, where you're sourcing it, because nowadays we see a lot of issues with sourcing of data. Have you come across any issues with that?

Interviewee: In general, we don't work that much with external data; so much of the data that I work with is generated by ourselves. So then you have some kind of trust in it. I think our marketing department will be more interesting to work with this question because they they at least work partially with external partners.

Interviewer: In some sense, the marketing department usually looks at external data but in some way, in innovation, would you consider some kind of data some or some kind of analysis, like what is happening outside that you will adopt?

Interviewee: Yeah, that would be more of a recourse as such. Of course we do quite a lot of the kind of studies where we try to identify different movements in the industry and so on.

And I think the problem there is that as with any work you get, you need to stay objective. And it is like the normal kind of trap you fall into that we try to evidence in data to support the argument that you have not staying objective.

Interviewer: Of course. Would you like mention anything else when it comes down to innovation and data and analytics or business intelligence in bigger terms? What do you think is more relevant?

Interviewee: I think when you talk about innovation, and I work quite a lot with on the Digital side of innovation, it is so much around data. And this type of experimental approach that we have requires so much speed because we want to have iterations of experiments in order to go somewhere, and that of course requires a lot of feedback in terms of data and then in terms of speed in that data connection as well.

Interviewer: Alright, so if you want to clarify the digital part of innovation or the digital side of it, what would that be, to put it in a few terms?

Interviewee: So it's more or less how we can increase our customer meeting and enhance that with digital components. So it's online or in the store or on your mobile, basically.

Interviewer: Okay, so I can take that as interaction with customers.

Interviewee: Yeah, and also with our co-workers.

Interviewer: Okay, so it's within company and outside as well. All right, would you like to add something else that is coming to your mind?

Interviewee: I think the retail industry is a very traditional industry where a lot of decision making is based on gut feelings. And using data in design decision on all levels, like both strategic and down to the operational level, has some difficulty in getting acceptance, because it's a lot of "this is how it has always been done". We know it's built into the spine of people, how you operate a business like this.

Interviewer: Okay, so what could be something that could be done to eliminate that?

Interviewee: So then it's back to the qualitative side, so design thinking as a method when you start looking at what kind of problem do people actually have. Because quite often we run into just creating solutions and throwing them in the lap of people and then they don't really know what to do with it. So design thinking brings in this element of empathy with the end user. That is really important when you build solutions.

Interviewer: Alright. The last question that I would like to ask is what kind of tools do you think you need or you use right now for your digital innovation when you work with data? What sort of tools do you usually work with?

Interviewee: We work with a lot of big vendors on the software side from Microsoft and IBM and also smaller ones like neo4j for example, they do graph databases. One of the things that we have struggled with a lot, and that we try to fix, is making data accessible. That is a big problem, that data is isolated in different silos, both functional and technical. And if you want to do something, like within innovation, then by default it's very cross-functional. We want to build algorithms that recommend products or something, maybe we want to look across many different functions, like we want to look at how returns are happening or how

products are selling or what are the delivery times of certain products, then we look across a lot of functions. So making data available in concepts of data lakes, for example, and then having people that can use advanced tool sets for doing data discovery, like some data scientists. And that's what we are working quite heavily on. And then it’s also our cloud solutions, like with Microsoft and Amazon AWS. There you get the full tools that they are also doing, like machine learning and deep learning and artificial intelligence. As long as you have the data available you can do a lot of things using the tools that is available.

Interviewer: So the tools, if you specify, would that be something like excel or Qlik or Tableau or some tools like those?

Interviewee: Yeah, of course Excel everyone uses. I think we have a full range of tools. We have the kind of business office things, we have the more BI-tool like Cognos and QlikView, but I think what we are working with more in my area that is more the advanced stuff which is more related into machine learning in Azure or in AWS.

Appendix 3, IKEA Interview 2

Interviewer: The first question is about influencers and indicators. Could you please tell us about your tasks or problems that you face in your daily work?

Interviewee: Okay, let's see where to start. So the fun part working IKEA is that there still is a vast amount of opportunity. So some of the problems we face right now is that data is seen from different perspectives and we need to improve what data we put in which context. So the context is the crucial part to work from to see how it can support the business model. So you can say that one of the challenges is very much on the on the backbone on the backend side; how we how we treat the data, how we treat the integrity of the data, the consistency of the data, and how we spread the data around in the IKEA landscape. It's not an easy task.

Interviewer: Okay so I guess a follow-up question is: have you faced any issues with these tasks before, and, if you have, how did you go about solving them?

Interviewee: That's a really good question. I think we have faced it over the years, many times for instance that… taking assets that we have in one place, making assumptions that we can use them in another context, not really understanding what the data is telling. We make the wrong decisions on the data. And we learn that over time by looking, and not only looking at the data, but also seeing the actual results, so the lagging measurements. And the way to go about that is to… that we have done in several cases is to really question ourselves amongst us as stakeholders to say "okay, but what does this data now really mean, and what does it mean in this specific context?" And very often when we challenge that we would say like "okay, now we understand we have a bigger problem than we thought, now we at least can avoid some assumptions and avoid some mistakes so where can we find the appropriate data to solve our specific case?" And this is… I'm not an IT architect. As an IT architect one of the main tasks is to identify the sources of data that is fit for the specific purpose. And that needs to be balanced in the same way as with the culture of trying to be quite fast, trying to embrace new ideas. So it's a balancing factor. So instead of just taking what the data you have, that might be one case, but very often it ends up that you need to go back and analyze it to see if is this now actually the right data for the right purpose. So that is one of our key… I would say problems actually, and the whole, let's say, vocabulary or business understanding of the data is a big, big challenge not only for IKEA I believe, but for any large company.

Interviewer: A follow up to that question would be; once you do have that initial understanding of the situation, what would be the next step, if you have this data that you need?

Interviewee: Yes, so the next step would be to see what is the potential to, in order to integrate and to get this data, depending on if it's in internal or external data, what interfaces are there: do we have already integration mechanisms to be able to capture and ingest that data, and also together with some principles or some, let's say, directions that what… let's say, modern integration concepts we are applying. Because we know from the history that a large company, when we build integrations, they will stick for quite some time, so they need to be what we call it: a sustainable implementation of that. So we would go down the route of identifying those sources, the interfaces, look at the legal aspects; is it ok, is it sensitive; we need to follow certain procedures how to store it, how to provide access to certain people, and then we would… if we go to the traditional side of BI, we would transform the data into dimen-

sions and facts and by that you would be able to build your data models and combine different data sets.

Interviewer: Okay, so in that same token: is there any point ever that you consider discarding data? For example, if is redundant or for whatever reason, and why in that case?

Interviewee: It's a really good question. So we have had, up until now I would say, a principle of taking in more data than the actual case has required. However, due to cost, due to processing and so on, we don't have a way to, let's say, take an entire system of data. So that has not been our goal either. But we have consciously, let's say, have a principle to discard data. For instance, as I can mention just as an example where I work here for the use cases, is that, let's say, you have a transaction that includes the number of attributes, and those are pretty much integers or that kind of type, and then you have an image. So depending on how big the size is of that image, maybe that image is not needed for this specific use cases right now. So we discard the image for now, because it might we might have a better storage optimization for images. So that's how we kind of think when we disregard some assets.

Interviewer: And also you said that you sometimes add more information than necessary. What is the idea behind that?

Interviewee: The idea behind that is that it's pure logic and that also experience on top of the people that that are making this decision, because let's say we have for example a chair that we're selling, and we put different price tags on the chair whether you have a your loyalty member or a regular customer, or maybe there is a discount on it. And let's say that would be, as an example, five different prices on this chair, but the actual case is requesting three of them. Then we will say “ah, but it's probably only a matter of time until that case will be evolved into looking at the other two”. So in that case we take all five.

Interviewer: So once you have this data collected, what do you do with it concretely, and also like a follow-up to that, do you ever reconsider the data as well? Maybe you say “okay, maybe this data wasn't so good after all?” Is that a thing that happens?

Interviewee: Yes, so I think I know what the question is about, but please correct me if I'm wrong here. But usually what we do, especially when taking in new data, is the data profiling on the data, because depending on the context, the data might have bad quality or good quality. And also we need to do the data profiling even on the existing data, because if it's a new context, the quality might be okay for the previous case but not for the new case. So we try to do that as an early step in order to find out: is there now a good likelihood that this data will actually help us in this case or not? And that is done long before we actually set up the integrations. So usually we take like an… we call it an extract or a snapshot of data, and then do the data profiling on that, and that then that can be iterated depending on which dimensions you would be looking at and how large the data set is, of course. So that is something we do at every time, I would say.

Interviewer: Also, how do you determine if a source of data is trustworthy; if it's useful or not, and if it's not, how do you handle that?

Interviewee: That's a tough one. So the tricky part with it… so if you take the internal case where we have a landscape of a lot of different systems, if we look at the whole data set of each system there, [there] is no complete overlap anywhere. But there are a lot of overlaps on

single attributes, for instance. So there are a number of aspects we need to think of. There is the life cycle of that particular system, it is the ability of how to integrate and what frequency of that data that can be delivered. So there needs to be a correlation to the business case; how frequent you need it versus the quality, for instance. Maybe it's better to have low quality and lot a big frequency if you use the samples of the data, so like in Big Data for instance or if we actually, for financial records for instance, then you might not need it so fast, but you really need a high quality of it. So because it goes to the books it needs to be correct. So it depends a little bit on the domain and also if it's a legal case, of course and so on, as well. In general there are a number of perspectives we need to look at here, and we also need to look at the governance of the data. So let's say it would be sensitive data or for legal perspective or financial perspective, it's really important that we have the data governance on that, because maybe it's easy to set up from a technical point of view, but if we don't have the right mechanisms in place it doesn't help if we have built the best integration ever. So we need to look at the whole aspect.

Interviewer: Can you tell us about some tools that you use?

Interviewee: Yeah, I can mention a few… so maybe some from a storage point of view there are multiple, but a big storage product is Oracle that we use. But in order to do the data management part we have the IBM tool suite; we use the information server, which is including the datastage ETL engines. We have the metadata repository, so for every data processing we capture a lot of data in one single place, and when I say one single place, I'm referring to the domain I now working, so we have unfortunately not, let's say, an enterprise wide view of the metadata as of today. And also we are different companies, so from other perspectives we cannot have them very easily, such systems. But that we have to process and we also have the embedded tools of the IBM suite to get the, let's say, the basic footprint on the profiling, on the completeness of the data; when it was updated, that we have track on, and this is very much what we call an application management task, to further secure that the processing is reliable and maybe, as you maybe know, we have some sourcing partners that help us to maintain that also.

Interviewer: I think that's pretty much it for the questions. Would you like to mention or add something?

Interviewee Yeah, maybe it could be... I think we touched upon it already; I think in this whole information landscape, let's say, I think IKEA is very domain structured still, so if we look at HR, if you look at finance, customer product, we have built up our capabilities per domain, you can say. And it's not very unusual, a lot of companies do this, but going forward we need to find a way of how can we be even more smart in the way we manage our data across the enterprise, actually. So if we look at the product information, maybe you know it's intra-IKEA, it's IKEA of Sweden that develops our products and the articles names, product names and so on, and this information where I sit on the retail side is absolutely, you know, necessary master data for us to have. So we need to exchange information between the companies anyway, but the tricky part now is that we need to do that this under legal circumstances as well, so it's not that we can, say, create our own project cross companies anymore. So this is a tricky little bit, but maybe that could be a value for you to understand, it's very much of a domain oriented information landscape that we have. It’s both good and bad.

Appendix 4, IKEA Interview 3

Interviewer: Could you start by letting us know what your domain is?

Interviewee: Sure, I'll try to keep it brief. I'm nearly 20 years in IKEA, and my role is BI and Analytics. I'm working across a number of different areas in business, so particularly in the business navigation as we call, it, area. We're dealing with financials and so on. And then I've also worked with some of the IT components like data warehousing and so on, so I have a pretty good understanding around of the BI world. Most recently I've been needing a transformation program within the company. And it starts from here two years ago. And [interviewee 2] has been involved in it and a few other people at IKEA. We are interested in looking how we work and, you know, what is the transformation that we need to take us forward. I think looking at the history, we've suffered from the same issues, some of it you've come across already in other interviews. We did a study which really highlighted some common themes, and what was wrong with the whole way we did BI. And then also to think, to have one eye on the future and what our future needs because I think we've been pretty much led down the road by vendors. You know, they tell us you have to have our BI tool, because that's the only way to do BI, and I think we've been a little bit conned by that and a bit brainwashed. That has resulted in some of the things that we found in the study. So that's a little bit my background. I've been working in the stores in the UK for 10 years and then probably the last 10 years working with BI analytics. So that's my area. And I would say even though I'm based in the business navigation area, we take a cross-functional view of analytics, especially within this program that we've been working on for the last two years now, so it's more about trying to drive innovation in this area.

Interviewer: So it's about innovation in IKEA?

Interviewee: Well, within the data analytics area, I would say. I mean there's lots of innovation going on in IKEA, but predominantly with the data analytics focus. And there's tiny examples I can give. I mean we're a very report centric company, though when we have a question there's always a report that's created for that. And that can be a recurring question that we have or it can be an ad hoc one-off question, but we still produce lots of reports. And we're very Excel driven. And I think especially in all levels, whether it's on a global level, on a country level, or even on a unit level, people are creating reports. So I think part of our work is looking at self-service, right. So what we're finding is that we have the same questions, for example in the stores, and the answer is "well let's knock up a report in Excel". And what we end up having are hundreds of thousands of Excel reports which causes quite a lot of confusion sometimes, because they don't always use the same data sources, they don't use the business logic, and so on. So you end up with lots of difference. And if you take sales reports, we must have hundreds of sales reports, and if somebody wants to say "well, what are my sales for last week", they could look at five or six different reports and all would get a different number. So this confusion is bred out of a lot of the needful for information, but hasn't been addressed, I'm saying in the best way. We're very silo driven, we have different functions create their own version of the truth, as it were, and it's part of the work we're doing. Now we to try to break down those silos and take a more community approach to data analytics. And actually it doesn't really matter who builds, but just share it. So if we have a good solution built somewhere, then share it. So this is a little bit of what we're facing right now. And of

course a lot of movement in the business; we've been pretty stable as a bricks and mortar retailer for a number of years. Now it's a big change to do e-commerce and multi-channel thinking. So it's a completely new business model, really. So of course data analytics has an important part to play in that, and our business users have a lot of the same questions, and so part of our innovation part trying to see where we can make life easier for people, I can say it simple as that.

Interviewer: So it's, what I would understand, is that it is about catering to internal clients within IKEA and try to make their life easier with analytics and data?

Interviewee: In every store they are creating their own terms reports, for example. So if we really understood what the questions were, in many cases it's never just one report that they ask for. If you think to yourselves, when was the last time you ran a report to make anything efficient in your private life, you know? If you're going on a holiday, or you're booking a restaurant, of whatever it is you need to make a decision on. You never run a report, right? You always got it available on your mobile device, on the internet, or something like that. So there are different ways of finding out information these days, and we need to embrace that and move forward. It does require some key components and foundation which is... maybe you talk about the link between business and IT. I think as long as we talk about business and IT as two independent bodies, then that's not helping. We have to have a more federated approach where we have business people that understand technology, and technical people that understand the business needs. So you need sort of one foot in both camps almost, if you want to be successful. That's an important point to bring out. If it's such a reliance on technology, whether is data warehousing, whether it's tools, platforms, whatever. So there's a very close marriage there that's needed.

Interviewer: All right, that explains the work that you do, I think the domain also. So I think you've answered pretty much what you tasks are, what the problem is, that you're facing in your daily work. So the next question would be about how you go about to solve these tasks, and what the initial process or situation might be that you come across?

Interviewee: We are still caught up a little bit in our old ways of working. I'm fortunate to have been working on this innovation project in the last two years, so I can maybe see a few things that we should be doing that we're probably not doing today. I think that the key thing first of all is to start with the business question and not start with "we've got tons of data, what can we do with it?", but start with a real business question, and realize that actually more than one function or silo have that same question or variations on that same question. So that in itself can start the process of more of a community approach. So if I take an example, if we're looking at sales theory, for example: so which products sell well together, what are good add-on products for that sofa or that bed, you know? These are common questions right throughout our business, whether it be the sales person in the store, whether it be a logistics person; you have to replenish it, or an interior design person; you have to make it look good and attractive and inspirational and things like that. The cost is in all levels, whether it's a customer that's interacting with our website and could get a good recommendation. You know when you go to Amazon and people who bought that also like this this. This is all based on the same analytics model and the data underlying it is the same. So and today we have issues where we might have 6 or 7 different things billed. I would say that that is one of the fundamental things to change, to start with the business question and to collaborate around that business question. And that would hopefully then lead to something. Like a better way of working. And again, it's about making life easier for people, and how we can do that well with data, where can we can immediate value from data. I hope that answers your question.

Interviewer: Absolutely. So how would you go about finding information for the given task or situation?

Interviewee: If it starts with the right question, and it might be a problem area like a business problem or an issue somewhere, and it might have maybe 50 related questions that we need to answer. Then of course the next question is: "okay, now we're clear on what the issue and the questions. Do we have the data to answer those questions?" In many cases we do if it's transactional data that we want you to analyze, but in many cases also we don't have that, and I think today's big picture is we always look into our internal data landscape to see if we have that. But we are moving, and [interviewee 2] is an architect so he would be able to explain a lot more. But what data do I need to answer this question? And then we need a more modern analytical workflow to actually process that through. Again, change our mentality from "okay, I need a dashboard and so we start a project for two years, and then by the time the dashboards built and then back, then the business has changed". So we want to move away from that. But start off with clear business questions and then get the right data to answer that, and then go through a proper analytical workflow with proper exploratory analysis and so on. So that's what is needed that's probably missing in many cases today. Some places do it do it pretty well, but then in general, I would say it's an area where we need to do some work.

Interviewer: So when you have data on your hands, is there any point at all where you consider discarding data for whatever reason, be it for redundancy or whatever?

Interviewee: Yeah, it does. Again, this is where some proper exploratory analysis is needed. If you have a clear question, then what are the variables that I need to consider for this and so on. But I think this is where we go into… now I'm talking generally; of course there are individuals and very experienced analysts that work pretty well with data. But on the whole, when I think of the functional perspectives that we have, we have the data and that has its complications, because it's not today a unified data landscape, but we're getting there. But we also don't necessarily have the right skill set to be able to proper analyze the data. And I'm now being very general, but you know that's what's missing. So we have a lot of business domain knowledge throughout all of IKEA. But when you come to the other two big areas of this field, which is more of the analytical skills, so do we have people with the right math skills and statistics knowledge and so on, to be able to do this analysis? And then do we have the technical skills to be able to, you know, maybe there's programming or some coding, or even just as simple as: "how do I connect to a database?". That sort of skills is sort of, a little bit missing. It then becomes a bit difficult to know how we actually analyze data properly. Are we analyzing the right things, are we making assumptions or decisions on the wrong things? That can be quite a worry, especially when you have different numbers and anything; which one is correct? Who's done the analysis on this? Show me the proof. That's a little bit missing. There's a big mistrust, I think, in a lot of the reports that come out, because we don't have, let's say, the modern analytical workflow where we need to have reproducibility and reusability and so on. That's missing. It's very Excel driven, as I said to you, so if somebody has some recurring reporting that they're doing, and they change jobs, then it's somebody else's job to sort of reverse engineer that excel file and look at all the formulas and everything and try to understand it. It's not a reproducible product. Again, it's part of our journey, deeper into analytics. But today, that's where we are.

Interviewer: Sure. So having that in mind; you say that there's a gap in knowledge. Do you continually add new data to that, or how do you go about handling new data that come in? Is it collected in a storage, or do you use it continually.

Interviewee: Maybe [interviewee 2] is a better person to ask that question to. But that one thing that we are not short of is data. And then it's knowing which is the right data that I need to answer the question that I have. And that can sometimes be a problem, because maybe you are making assumptions on: why are sales in decline, maybe. That could be one question, and then, well is it the weather, or is it this, or is it that, or the other? You don't really know, so you need to do a lot of this analysis, and then maybe you get rid of some data that you don't need. But there's always new data coming in and when we now need to change the business model and look more from a customer perspective. I mean, what is that data that we are missing today? Well, help us to actually improve our business. I know that a lot of the customer data that we get, whether it's data from the call center, or emails, or whatever it is, it's done in pockets, and again, it's something that is sort of work in progress. From an architecture perspective, [interviewee 2] would be able to explain what we got in the pipeline. But we need to change the business model and we have to find ways, especially from the customer data side. I think it's pretty good that our transactional systems and our enterprise data warehouse is pretty robust, but it's the unstructured data, as they call it, or the external stuff that, "how can we get off that, and make sure we are getting the right data?" That's a bit of a challenge now.

Interviewer: By the same token, I guess you also reconsider the quality of the data that you previous selected for a given task as well, I suppose?

Interviewee: Absolutely, yeah.

Interviewer: Okay. And also I would like to ask you about the source of information. How do you how to make sure that it's credible or trustworthy? And if it's not trustworthy, how do you go about processing that?

Interviewee: I think with the sources.. we have really good measures for data quality. So we know if inputs are corrupt, it can be pretty easily identified by the business analysts. I think within our own systems, it's like, what's good data quality? But it's good enough, is the typical answer there. But because a lot of the other systems it's hard to put that trust into those sources, know? Should I use that source, or should I use X or Y? Again, this is where the exploratory analysis.. what sort of variation in the data do I have, and what can I trust? I think a lot of the trust issues internally come not so much from the sources themselves, but the fact that we are using different sources in the reporting. So sales report A gives you one number, sales report B gives you a different number, but they are coming from different sources and maybe with different business logic behind them. A lot of confusion and mistrust is more in the reporting rather than on the data side. But I would say that, of course you will always get errors, but on the whole, I think the transactional systems are pretty robust.

Interviewer: So along the same line: have you ever encountered any issues regarding relevance of data?

Interviewee: We sometimes, you know... what variables do I need to consider? I mean, we are a little bit blind sometimes. If I was to think recently, we posed a question to some analysts; "how do you predict sales?". It was quite varied, the answers that we got back. When you base your starting point on your last study, then you are already on wobbly ground, I think. Is it relevant that we took X amount last year as a base for my prediction for this year's sales? I mean, it's not maybe relevant for this case. So I think there's still work to be done in many cases there. But it's again just an understanding of: "have I got the right data to answer my question?" And maybe we need to make sure we have a better understanding of what the question is. Maybe that's the failure there, if we do have one. You get assumptions thrown at

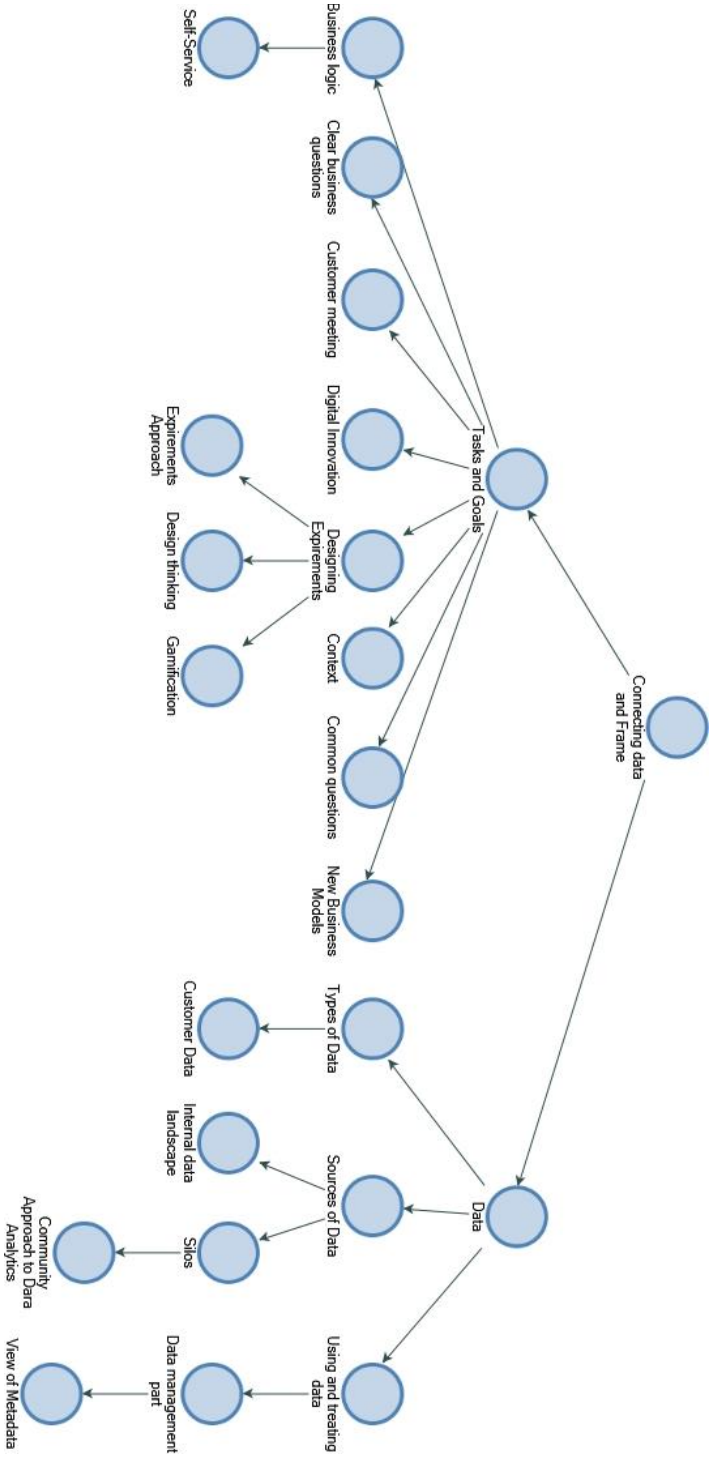
you that it's the "whether", is it this or that, but it's never like, "okay, prove that to me then, show me the analysis and improve, what is the margin of error here?" That's not always so usable. A lot of it's historical when we've done it like this forever, so we continue to do it like that. There are things that we need to change, some of these ways of working, I think.

Interviewer: Sure. Can you just also briefly tell us about the tools that use? You mentioned think briefly the beginning Excel. Do you use something else as well?

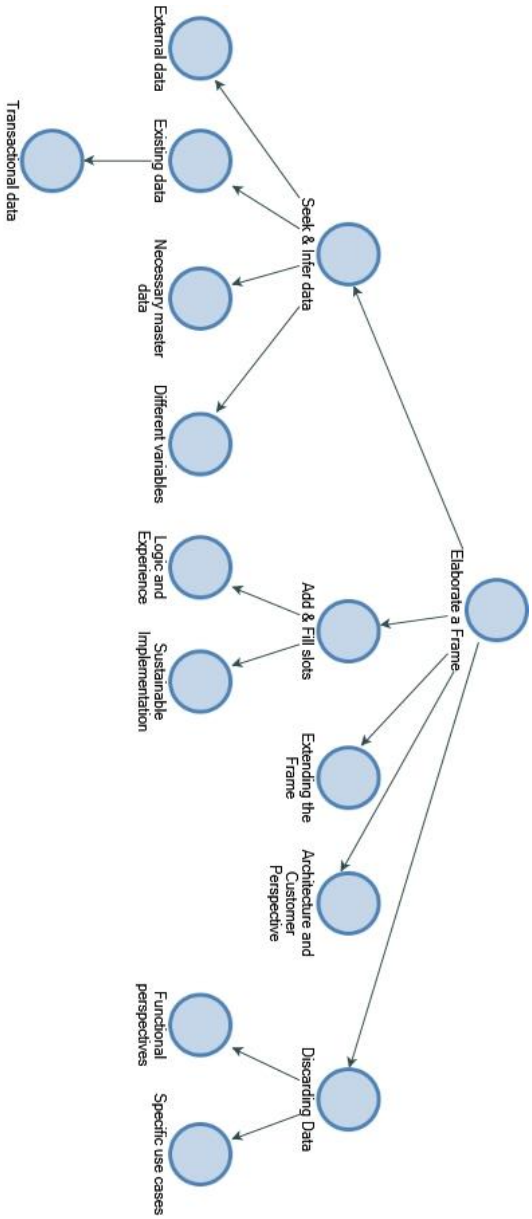
Interviewee: I think Excel is probably the most widely used tool for providing information. Of course it's easy to use, everybody knows how to use Excel. But it's also very error-prone and very manual heavy lifting and so on. And then we have some enterprise tools, BI tools, we have IBM Cognos, and we have QlikView which is based in Lund and from Qlik, and Microsoft Power BI. What you find is, again, we had an approach in the past where this one-size-fits-all... so Cognos was really pushed across the Company. Not everybody likes Cognos, and it doesn't lead all the jobs that needs to be done. So this is where companies like Qlik come in and offer a different solution for a different purpose which is much better. And, you know, there are a number of tools we use, and I try not to focus on the tools so much but rather the information that you get out of it. Unfortunately too much emphasis is placed on the tools. But again, I think this is where we've been led on by vendors. I mean IBM really couldn't care less as long as where're paying the license fees, but when it comes to how we want to work going forward… if we're publishing information to 150 000 people, we shouldn't be paying license fees for that. You should be putting it in a web page or something like that that's free. So then it's more about the consummation of the reporting in the information, and the modeling, and you know, something can be done in tools, but I think there are there are new ways to present information to a lot of people. And because there are different groups within the company, different teams are using different tools, maybe locally bought tools, or open source. A lot in the analytics teams are using Python and R and things like that. If you can find a way to get rid of Excel, then thumbs up.

Appendix 5 NVIVO Coding as Mind-Maps, IKEA

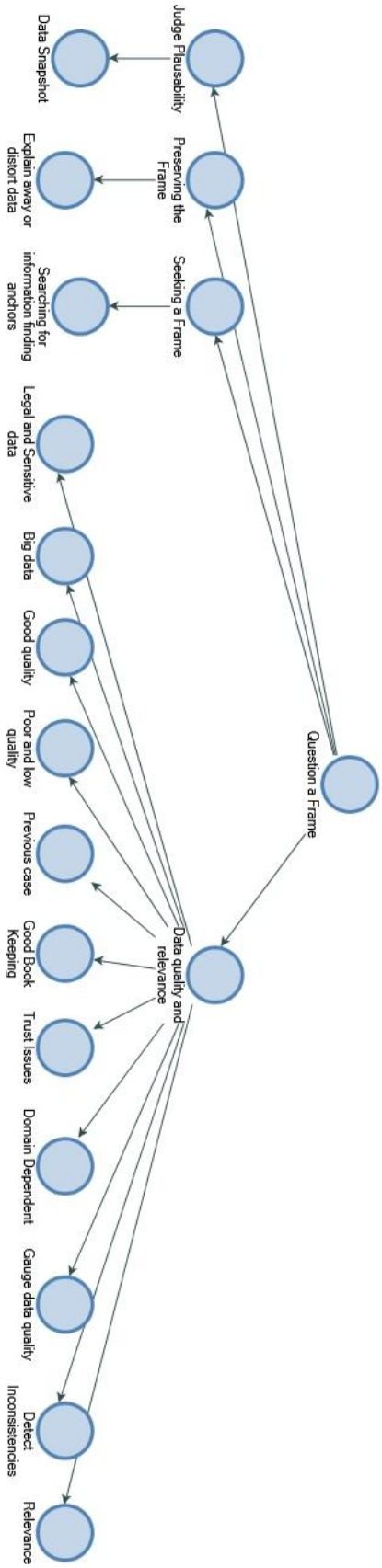
Connecting Data and Frame Coding - IKEA



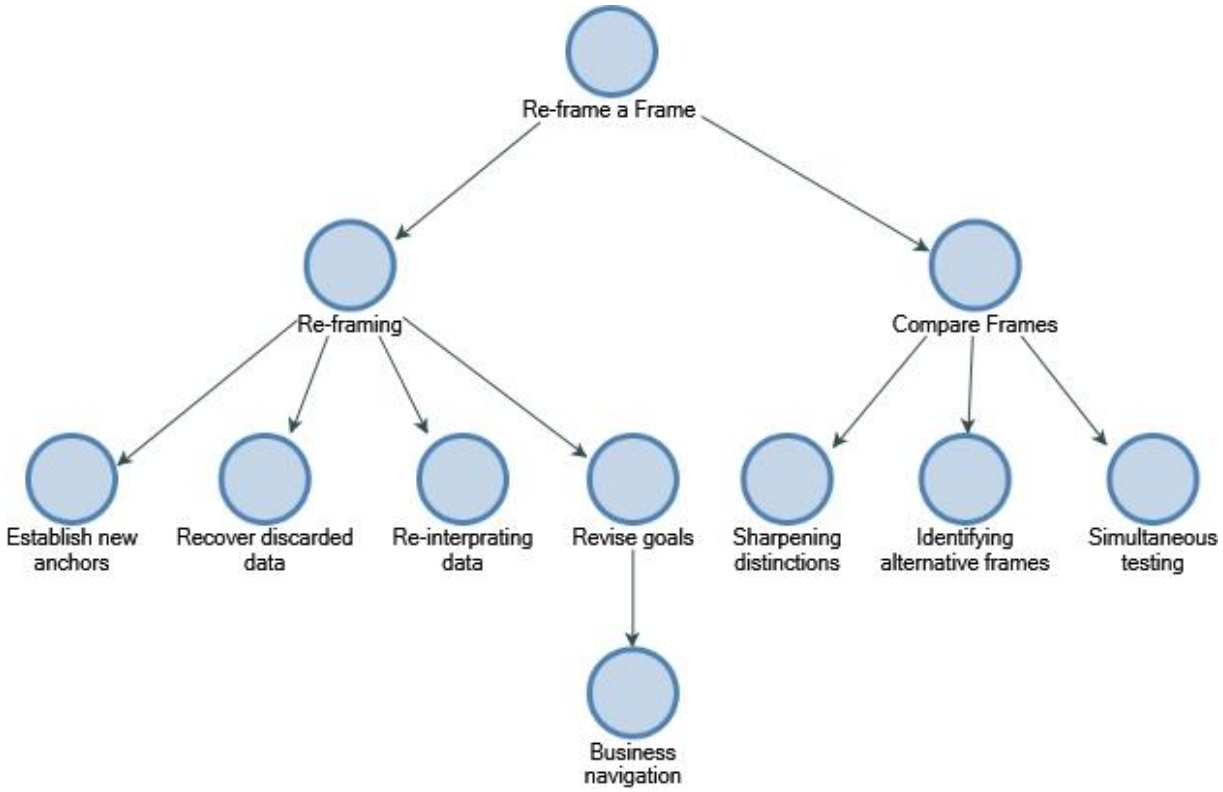
Elaborate a Frame - IKEA



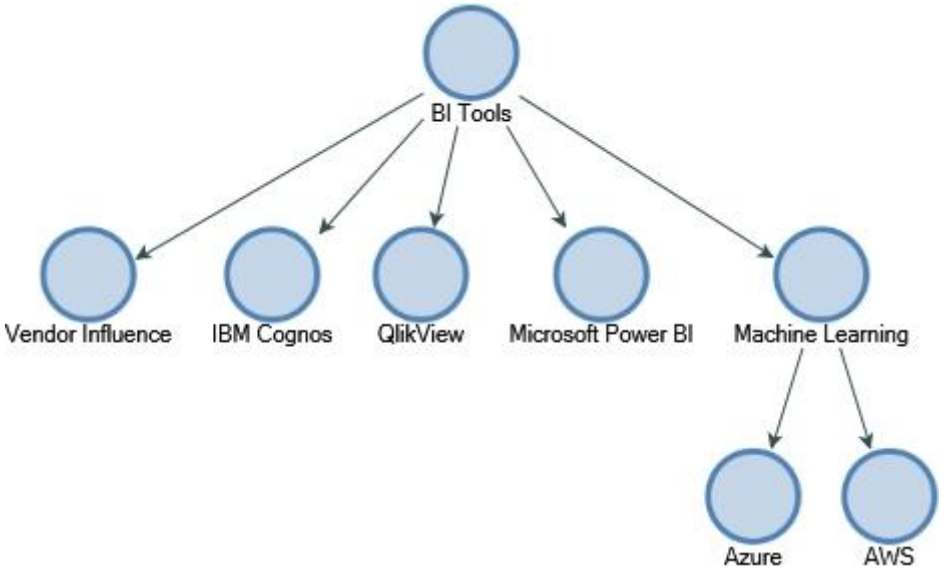
Questioning a Frame - IKEA



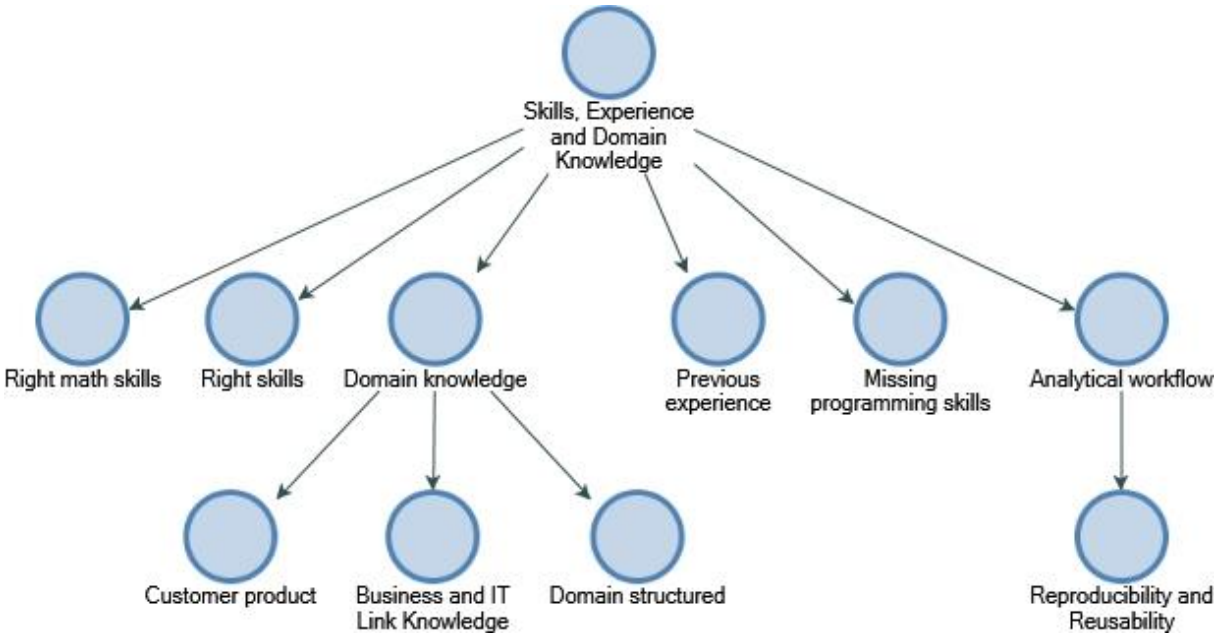
Re-Framing a Frame, Compare Frame - IKEA



BI Tools – IKEA



Skills, Experience and Domain Knowledge - IKEA



Appendix 6 CDON Interview 1

Interviewee: I would like you see here we have all the data that coming backwards. Actually I have from almost beginning of 2001 when we started the company, and it's a huge database. So we can see for example new customers in March 2018 and this by country here. In Sweden we have 22,000 new customers.

Interviewer: So it's which year?

Interviewee: It's only this month. We put two thousand new customers.

Interviewer: So that's a big number

Interviewee: Sweden is of course the biggest customer; it's where we focus the most. Norway Finland and Denmark are pretty small in numbers

Interviewer: It's still not bad, 6,000 in Denmark!

Interviewee: But you see here the average value of the orders, it's not so huge. This is the total [Shows QlikView on screen]. It's not only about the new customers.

Interviewer: I think you can see here Denmark is slightly higher than Sweden compared.

Interviewee: Maybe they buy more iPhones.

Interviewer: But these are all online shopping, it's not offline?

Interviewee: Yeah of course. You can filter anything here, if it's voucher, if… some guys wants adult/erotics and we have to accept that, so that's a special filter in the database so we only merchandise to these customers that have accepted that kind of thing. Of course we have to work with GDPR, so we can only save this for two years. These special things like postal code or name or age, so you cannot go into detail see specifically if it's this customer, or "I love this". You can see female or male, and which language. You can pretty much scale it down to anything you want, how the customers purchased. And then of course it's difficult to know how to use this data.

Interviewer: Then it's all internal data at the moment

Interviewee: Yeah exactly. It's a little bit slow here since it's so much data. You can see the emails and customer number and everything.

Interviewer: That's massive, actually.

Interviewee: And here we have cohorts' analysis. We want to see when the customer did their first buy. These customers who purchased in March, 93000 of those 229 made their first buy in 2012.

Interviewer: So it's like a comeback?

Interviewee: Yeah, exactly. We want our customers to come back of course. The first year they are very expensive to purchase just to get them into it to be a customer, we sent the voucher and so on. You get this email all the time.

Interviewer: So some day or another they would come back?

Interviewee: Exactly, hopefully. That's when we make money on customers.

Interviewer: It's just like with Netflix, I decided to try, and when it expired, they sent me another email. They still give you another try, and won't stop until I really sign up.

Interviewee: It's the same for almost any commercer. I mean, in my Gmail I have filtered everyone on the campaigns, since it's never ending. There's the other cable company Nelly, you know those? Clothes. They send emails all the time. Zalando also. Then you have Dustin which is competitor to CDON. Because CDON is very big. Our spectrum of articles we have all from clothes to computers.

Interviewer: CDON itself? Because Nelly has it, it's same group company.

Interviewee: Not everything since we are a marketplace, a lot of the merchandisers are connected. We get commission. We brand their products on our site. So if you're going to buy furniture, for example, we are not distributing furnitures, it's not the company. I can show you if you go to the website, you can see in the article there is a line saying if it's a CDON product or merchandise product.

Interviewer: It's like Pricerunner or something?

Interviewee: Kind of, it's like Amazon, we want to be a small Amazon. You can see here this is sold by TechTech. So it's another company, it's not CDON itself.

Interviewer: Right, do you get commission on this?

Interviewee: Yeah we get a commission on this well.

Interviewer: That's cool actually, it *is* like Amazon.

Interviewee: On average we gain like 10% on this product. So it's a good margin for us so we don't need to take the risk either, getting it in stock and handling it.

Interviewer: I mean the logistics supply chain is the biggest cost.

Interviewee: Yeah it's a huge cost. Then in the future our goal is to have all these products so you can be like Pricerunner maybe, to compare the prices in the site, where you have a computer, for example, which is CDON for example, and maybe also a merchant, so you can compare these and we can adjust the prices so we can make the margin there. But yeah, it's a big step there.

Interviewer: Do you plan to open small member's company website so that people can open their own selling portal for those who don't like Amazon?

Interviewee: Yeah I guess that could be next, but it's also difficult because you need to have these regulations. And of course you cannot take in anything. I think we have like 1,000 merchants at the moment that we are negotiating with that need to go into the website, because we need to filter so the product is correct and everything the price is correct. So it can't be like civilians putting up stuff, it'll just go crazy I think. But of course that could be a way.

Interviewer: But with all of this data, are you the only person working with this?

Interviewee: No, not the only we. We don't only use QlikView, we have Google Analytics also from the marketing department. But me, I'm only into QlikView.

Interviewer: Okay, but why is that? Are you only focused on just looking at customer retention? And you say business control, what is the spectrum or the scope?

Interviewee: It's really everything. Here you have a purchase, cohort, the status.

Interviewer: All right so that's more like this is controlling, mainly the operations?

Interviewee: Yeah exactly. If it's a CDON Plus customer which is the customer who has signed on to us paying like 150 SEK one-time fee, and then he gets free freight cost. Here you see membership, if you pay 199 SEK we get free Freight and some kind of return when you purchase. So you can use this purchasing.

Interviewer: Actually that's very good. So this membership it's like one time?

Interviewee: It's one-year. Usually it's 299 and now there is a special offer for 199. Then you get free freight kind of return on your purchase.

Interviewer: That's a very good idea actually.

Interviewee: Yeah of course. If you want to keep the customer it's very good.

Interviewer: It's also like you can cover a little bit costs of your returns.

Interviewee: Yeah exactly.

Interviewer: There are a lot of customers that buy and return. In e-commerce the returns are really massive.

Interviewee: I don't know how much the return rate is here but I know Nelly had big problems in the first quarter. I think that 30 or 40 percent, because they had some special offer at Christmas that the customers could return up to 90 days and that costed them huge.

Interviewer: That's massive. It's because also when there is some like occasion or something like youngsters, they order, they wear it and send it back. They put the label in some way correct. Because it's online it's not tangible so they try it. It's a huge problem in reverse logistics; how to return it back.

Interviewee: Usually if you don't know the size you order like, three articles of one clothing.

Interviewer: Actually, in my first masters in logistics we did a study for this. I ordered something and tried to return it back and I just saw the process how everything goes. It's a bit problematic because everything is on paper and you don't know where the stock is. Because a lot of stock is in the supply chain, it's down there. So you can't use that actually. So then you have a buffer and then you really need to balance the distribution. You're aware of that.

Interviewee: I know for example H&M, when you buy something there in the store, previously you couldn't return it to the shops for example, that's crazy. They have such a huge network of sourcing, they don't connect it to the approaches.

Interviewer: But in CDON you can return things through post note, right?

Interviewee: Yeah.

Interviewer: The distribution is also by post note?

Interviewee: Yeah.

Interviewer: Is it in Helsingborg?

Interviewee: Our oldest stock is in Ljungby. And then we have dropship companies, which are other warehouses in… I think it's in Helsingborg, I suppose. I don't remember the name, "Bright Star" or something?

Interviewer: Okay, I haven't seen "Bright Star".

Interviewee: It's for the computers.

Interviewer: Usually Helsingborg is massive for fruits and vegetables supply chain. So then we have EverFresh and ICA there, and these big Giants who are taking care of COOP and ICA stores. Even Malmö is growing massively. I think I heard IKEA is also opening another warehouse here.

Interviewee: It is?

Interviewer: Yeah, distribution here in Malmö. I just saw something on LinkedIn that someone posted.

Interviewee: Yeah, IKEA is huge. We are a small player compared to those companies.

Interviewer: I actually worked for because NoWaste, which is also providing service logistics to TradeMax. So the production in there, actually I designed the warehouse for them.

Interviewee: You can see here, furniture… maybe if I just type sofa… they have some other brands, not only TradeMax

Actual interview:

Interviewer: So the first question is about data and how it is analyzed and interpreted. Could you please tell us about your tasks that you face in your daily work? You can take a task and relate that data and say how you would you go about process that the whole thing.

Interviewee: Yeah, it's like for example last week, we have this.. you have had this cost with the voucher codes that were given out, then we need to analyze the customers that use these codes, which ones have used it how much they still have left. That can be a big process, and then of course you have all the data that you need to gather, when was it used, and I don't have to recalculate it, how much they have used of this. Then of course QlikView can be a very good tool if you have like 10,000 customers buying a voucher code, you have a huge data and then we can scale it down with these applications. [Shows QlikView on screen] We can see if it's a voucher; yes or no. We can filter the data for example if we have all the data 100 000 customer orders we can easily find that specific information. So QlikView is of course good to use when we need to scale it down, but then we need to maybe use it in Excel, but of course the first steps decreases it very well, I mean, especially for us, with so many transactions and orders. That was not the case for example in our previous companies. We didn't have that many customers and orders in this company. Here QlikView tool this a very good at scaling down the data processing.

Interviewer: Some of our questions you already answered, so we've not going to ask them again. Now we know how these tasks are related to your domain, which is what you mentioned before, the operation business control inside.

Interviewee: It's a lot connected to the costs, I mean, since we're in controlling because of follow-up. But of course also how we can profit our sales and this information about the customers.

Interviewer: So the decision-making is going around the costs around operational cost?

Interviewee: Yeah

Interviewer: How well do you think you are prepared for these types of tasks and situations? Do you think something could be done more?

Interviewee: I think a lot can be done more. Like you see you're on the table we have so much noise everywhere. We don't have like a specific filtered tool which we can go in and see our profitability yesterday or marketing spent for example, we cannot see so accurately.

Interviewer: Okay, so the data is not in one place?

Interviewee: Yeah, a lot of parts. This is for example from Google Analytics [Shows on QlikView]. Here we can see the traffic in April. Here are some data, and then you saw in the marketing app there is some other data. We have so many sources also. We don't talk like one system where we gather all from. Maybe we do sum up everything. And of course it is like this in a company when we are growing all the time and we're putting new things in, like the marketplace parts. And now we have launched a business-to-business site last month. We launched it and then afterwards we were “how do we handle the data?”

Interviewer: So that's like sinking a lot of other data. Because it's still the same stock, the same flow that you work within different areas.

Interviewee: And it's a lot of quick fixes usually just to get the information.

Interviewer: I see that you have Facebook Denmark.

Interviewee: Yeah, we folks that are on marketing this year on Internet, Instagram… Last year we had a lot of TV's for example. A lot of social media.

Interviewer: Do you have a student Mecenat-deals?

Interviewee: Yeah I think we have free freight or something if you're a loyal customer, or maybe you know a CDON plus member, some rebates on that I think.

Interview: Alright, so I'm going to the next question. We were asking these questions which are mainly associated with what are the influencing factors and indicators, which are these ones according to your task. So I will go further because there would be some questions which are unnecessary to ask since you've already answered them. I think you also have answered how you would go about information finding, the data given the task order situation. What about add discarding the data; taking it out. Does it happen?

Interviewee: Yeah of course. Sometimes like I said there're a lot of data that's always data that will… so in the first year, we take it out in Excel and try to compare and see if it's reasonable and so on. And then maybe sometimes you cannot see a connection if it's reasonable or not. You cannot maybe analyze it and use it, so that can be the case sometimes, yes. It's difficult to relate it to something, especially with this customer behavior. You have to be really, really secure, because of course it's huge decisions, especially for a company like us who have put a lot of cost in marketing. We really need to know what we're doing, so not spend too much. I think marketing is ours. After sellers of course, since this is the biggest costs for the company.

Interviewer: Marketing is huge, especially in an e-commerce context.

Interviewee: It's like 10% maybe, I don't know. It's a huge cost.

Interviewer: All right, so moving on to another question. What about the quality of the data? Do you ever reconsider the quality of the data that you selected previously for a given task?

Interviewee: Like I said before it's comparing the reasonable data to see if it's accurate. It's sometimes difficult to see if the quality is good. Of course in QlikView you always have to question yourself if the numbers are correct. I remember a couple of weeks ago for example for digital games, you know these when you purchase a code for a piece for a game or something, and we had a problem with the purchase prices in the system, so we got a negative margin. But that's only the numbers in the report, because it didn't make a change in the ARP system, which we didn't' catch in QlikView. We had the wrong numbers showing up. But of course in that way it was easy to see because it was like minus 50 percent margin, this was impossible.

Interviewer: In reality it's not there?

Interviewee: Exactly. We see it in reports and then when we compared the booking at the end of month, it's not negative margin, it's busted. So in some cases it can be easy to find it, but of course some cases that can be very difficult when you have, like we saw before, you only look at the big topics of the channels of your countries, you don't really see the data at the lowest level. When you have so many transactions it's easy that you don't catch everything, so that's maybe the question for us – to find out the exact numbers.

Interviewer: That explains that. I think you have told us about the source of data already, trustworthiness which is the same question and the relevance of it also. Have you in some instances considered solving the problem in another way?

Interviewee: Yeah, we always try… maybe you use the same way if you know it's a good way, of course. But since we are a team we always try together to brainstorm together: "okay, how can we do with this one if it's a better solution, how can we find it?". But of course, sometimes if you know it's an easy way and you have a tight schedule, you go with that one. So maybe you're not always thinking out of the box.

Interviewer: So it's like you don't need to really reframe the concept that you have, but then you're like "okay maybe that's the best business practice"?

Interviewee: In some questions, yes. But since it's a new team also you're not working alone. Maybe I question sometime because of my knowledge from my previous company like "why do you do like this, why don't you like this instead?".

Interviewer: And it's important because you have previous experience in logistics and supply chain as you mentioned. That has implications, like your previous knowledge that you can bring in to reevaluate to reframe the questions or the problems that you have.

Interviewee: Yeah, that's why I think it's good to not be in the same company all the time. I mean, coming here I think is a big step and a good step in many ways. But of course it can be… I mean we are quite young team here. We don't have that same experience. I remember at Skånemejerier for example, a lot of my colleagues were like in the 50s and it was up to 60 years old, so they have been there before, they know the business of dairy production for example. But here in this kind of company, maybe you need the same way of thinking, because you are just not that old yet. So it's depending on the company, I think.

Appendix 7 CDON Interview 2

Interviewer: What kind of role do you have in the organization, and why do you work with analytics in data?

Interviewee: So I work at the economic department, and right now it's in between accounts receivable and controlling. So the data analytics at accounts receivable is mostly payments from the customers. We handle a lot of payments. and then on the controlling side it's a little bit more of different data; looking at if something is worth doing or if something is bad. So on the control side is it's a lot more broad, on the accounts receivable it's very focused to payments.

Interviewer: Can you shed light on what your role is in the controlling side?

Interviewee: Okay, it's still mainly collecting data and checking that it's alright, that we know why these transactions happened. So it is it's not that much looking forward right now, it's more checking so that we don't have any leaks that we should not have. So for example if in our warehouse if there is something, that we're taking something out of the warehouse that the customer have not bought, then of course then we need to know: "Okay, why did you take this out? Was it because it was destroyed in handling, or is it going to some marketing campaign, or why did we take this out?". So we are just making sure that we should not have those kind of leaks, that's one part. Another part is to make sure that, for example, when we sell something, usually there are agreements with the companies that sell the items, so we can have a lower price because they help us with a part in it, for example. So we need to follow up on that we actually get in everything we want. And of course that's the purchasers job to do, but someone needs to also maybe check that it's ok. In the end we get in the whole of the sum. So that's two examples of the controlling side. But like the name implies, it's more of a control that we that we don't leak anywhere or that we miss out on something. On that accounts receivable side it's: "Okay, we have this much money on the bank, how much did we expect?". And then of course see if there is any difference between these and we of course check it out. But usually it's used: "Okay we expect 100, we got 100", and then we book it, so that's pretty straightforward on the accounts receivable side.

Interviewer: So a follow-up that is: how do you go about solving these tasks that you are engaged in, meaning the initial process?

Interviewee: Most of the processes are quite routine. But then like I said, we need… something happens quite fast, then it's: "Okay, how do we solve this?". And then of course you have something in the back of your head that: "Okay, maybe it looks like some other process we have, maybe we should try to make it look like something we already know". Then of course if it's completely a new thing, then it of course depends on the scale of it and where we get the information. Somewhere there is like, we need to know how much money we get in for it or how much it would cost. So somewhere there is information in and then we just need to maybe mimic some other process, you'll find another way. But most of it is quite routine, I would say.

Interviewer: Do you consider yourself well prepared for these tasks?

Interviewee: Yes, I would say. We have a quite good learning process when you get into a new role. Of course it depends on how you get it. Maybe there opens a completely new position that you should fill. Then maybe you have make your own schedule, but if you're filling in for a person and maybe go to another job or got a new role, then they teach you so that you can fill this position. And then of course depending on the timeline it can be a month or more. But the step over to controlling, for example, for me now it's several months of learning that you get one thing to do, when you try that and then they add new stuff. And sometimes it's new processes. and then you will have to find your own way based on what you already know. But I would say that we are well prepared on the at least basic stuffs, and then when there is new things and maybe it's a little bit more ad-hoc.

Interviewer: Suppose you had that initial understanding in the beginning: how do you go about doing this task? You mentioned ad-hoc learning for example, is that from the initial get-go?

Interviewee: I would say after the business studies at the University and then starting at the work, there is not much that you use from your studies when you go into a company, because the company and the things or the rules are already set, so there is a way of doing it. Then of course maybe you can come in and think "Why are we not doing it this way?", then it is like "ah, because we have done it 10 years", and no one have time to question it. You have a small understanding from the University on how it should work, but it's usually at least here, it was very different to how they do it. But then it's like I said, I have a good learning experience in the beginning here where they taught me how they do it. And then you do it in that way until you feel like: "Okay, now I understand this good enough that I can start implementing my own ideas". So for example, in accounts receivable it's usually making sure that everything that we kept on the bank is booked, but we get a lot of payments from so many different ways and we have so many different foundations it's not always easy to make sure that it's completely correct. Sometimes it's alright that if there is a small difference, and how we make sure that everything is alright, that process when you started to understand it, then you could start improving it so it works better for me. Because you take over a lot of documents from the person before, and maybe in their world this was the best way to do it, and then invites another way of doing things.

Interviewer: So in that same token, do you ever consider discarding data for the tasks, and why in that case?

Interviewee: I would say that sometimes we have too much information. When they started a process it was usually like: "Okay, we have all this information, let's just put everything in". Then of course maybe not all of it is important for the things that I do. Maybe there is someone else sitting at the development department or purchasers that use, let's say, this column of information, but I'm only interested in the first three. So of course then I don't really take any notice to the other information, it's the information that I will need. But do you mean like if I get different information?

Interviewer: It could be, like redundant information, or what you would consider unnecessary, or like it's you mentioned in the beginning; too much information.

Interviewee: I get in the case when you get too much information then it's just… you take the information that you need to do your part, and then of course if it seems that something is very wrong or makes you question if the information I need is correct, then of course you

have to look into it. But I don't always look at all the inflammation. That's not possible in all cases.

Interviewer: So is there any process you go through, or is there any way you think about data? How do you sort it through?

Interviewee: I would say in the routine stuff then it's just: "Okay, then you more or less have all the steps in your head, it's like "Okay this document, I need these columns" an so on, and then no more thoughts exist, the other information is just there.

Interviewer: So I guess another spin on that would be if you ever reconsider the quality of the information that you receive as well?

Interviewee: That's also if it's routine stuff, then usually something you have somewhere in your mind like: "Is this amount that I get reasonable?". If you want a hundred and you get a thousand, then something might be wrong here, and then you start looking it through. So in the routine it's just what you have in your back of your head. Sometimes we also have information from two different sources that you match together, and if there's a difference then something is wrong. So then you find it out that way. But usually it's more or less that: "Okay, is it reasonable?". If it's something that we don't have in a routine, then it's more like: "Okay, based on what I know from the other things I do", and that little experience that you have, then "Okay is it reasonable?", maybe asking a colleague: "What do you think, is it reasonable that we get this amount?". And also of course you have to validate your data, because we have a lot of data, you know. And maybe it's better to get the data from another source, because that data have already filtered out this and this. So yeah, that might be a problem when it's new things come about. First, make sure that you get the data from the best source, because we can usually get data from a lot of sources.

Interviewer: There's an element of trustworthiness I suppose as well, right?

Interviewee: Yeah, of course, but a little bit of experience that you feel like: "Ok, it's reasonable", and then asking someone if you're unsure if this is the best data for this thing.

Interviewer: Just like you mentioned it's new things, you need to consider if it's just the right data.

Interviewee: Yeah, because it might be that if we have three different systems where we can get this data [from], but there are small differences between the systems, then ok, which one is the best? Sometimes it's good to ask someone else like "Do you think that this data is the best to find out?".

Interviewer: So to spin that another way as well: is there any point in time where you have had any issues when you when you sorted through data, for example?

Interviewee: I think same again for the routine stuff, then no problem, I would say. But when you're trying to make an analysis of something, then… it happens of course. We have a lot of data, but it happens, that ok. I pick a little bit of data from this one and a little bit from this one, But to be able to get the data I need. And then sometimes you have this, and then you're like: "I would need this as well". And then it starts to get difficult to get the data to match the different datas to get what you want, so then you have to be really careful with if the data is still correct. It gets difficult to follow.

Interviewer: So have you ever considered come up with a completely new solution because of that, for example if there's conflicting data, for example?

Interviewee: We are still a little bit restricted based on what systems we report everything in. So it needs to be able to push into this system. So you can't go completely out of the box. I can't really come up with an example of where completely changed something, but it happens all the time that we started picking the data from a new source. I get the feeling that we are working more and more towards getting everything into one source, and trying to get work less and less in other systems.

Interviewer: Can you tell us about your BI tools or business intelligence tools?

Interviewee: We use Microsoft Navision, that's the main reporting tool where we book everything. But then of course we use other ones like QlikView. Right now it feels like more and more is going into QlikView.

Interviewer: Okay, why's that?

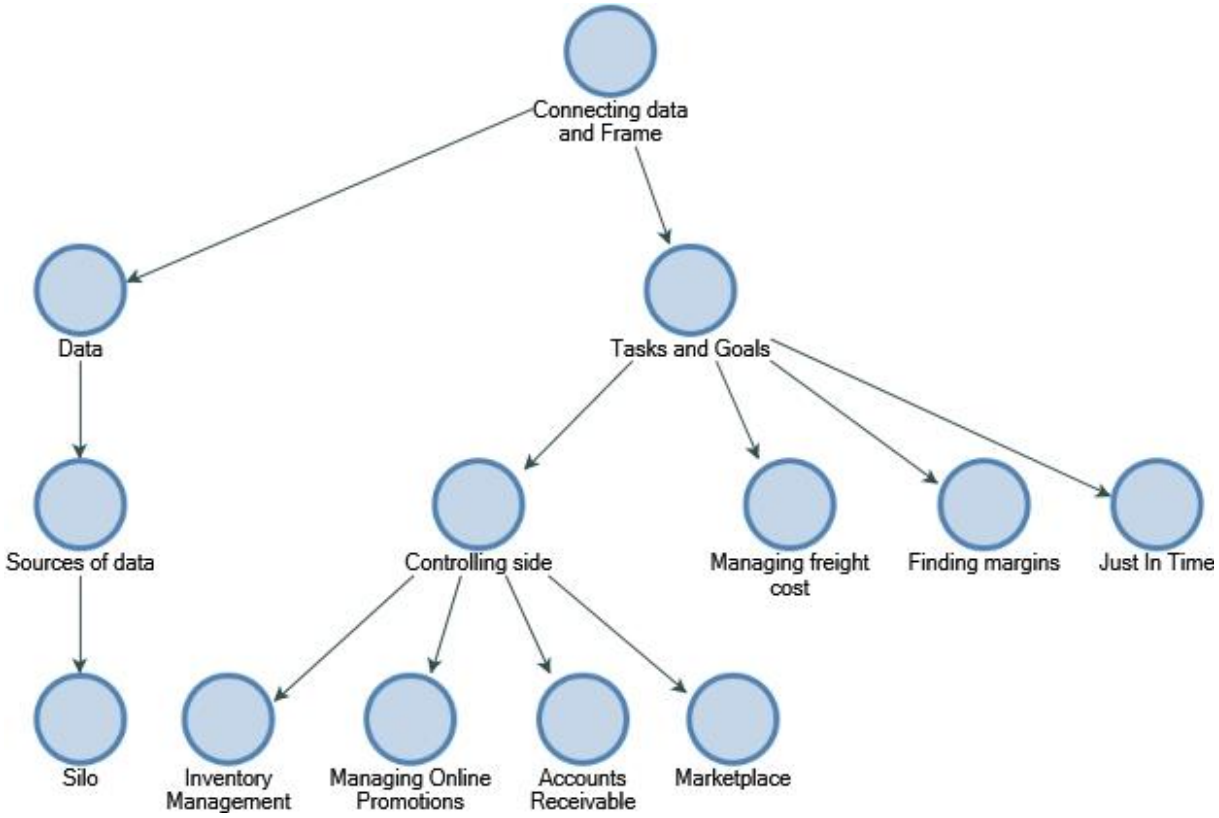
Interviewee: Because it seems to be easy to get information from other systems into this one, and then get a good picture of the whole, instead of having ten different systems that pick a little bit, it's better to have one.

Interviewer: So what kind of sources do you believe you think you use right now in QlikView?

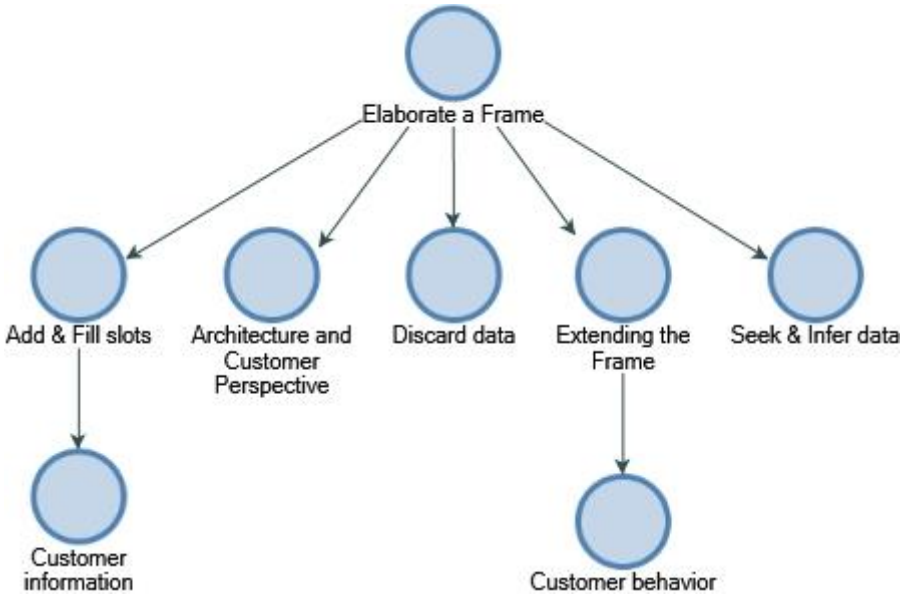
Interviewee: It's mostly sales, data, and warehouse information. That's the main I use right now. But there is a lot in that, you can get out to more or less whatever you want in it. It just needs to get the information from somewhere, but you talked with [Interviewee 1], so I think he have talked a lot about QlikView. So he knows more about that.

Appendix 8 NVIVO Coding as Mind-Maps, CDON

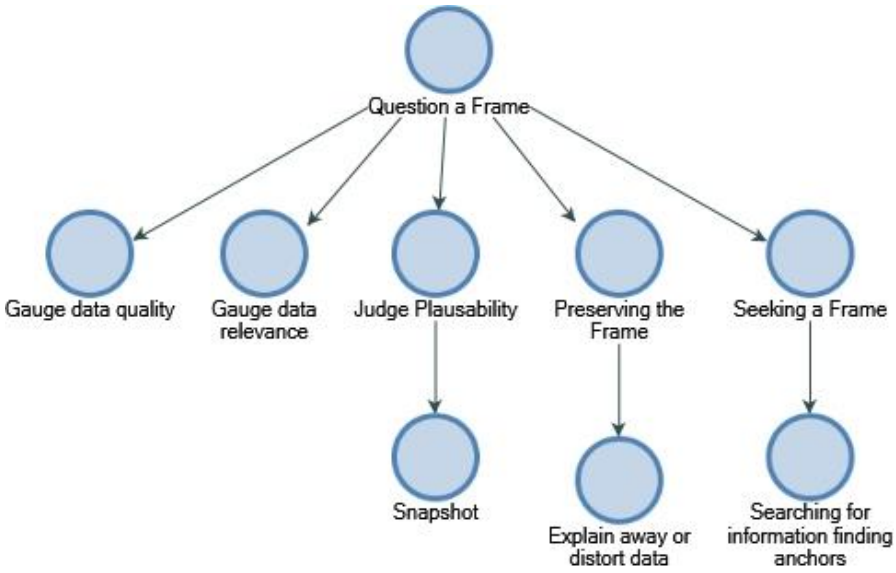
Connecting Data and Frame



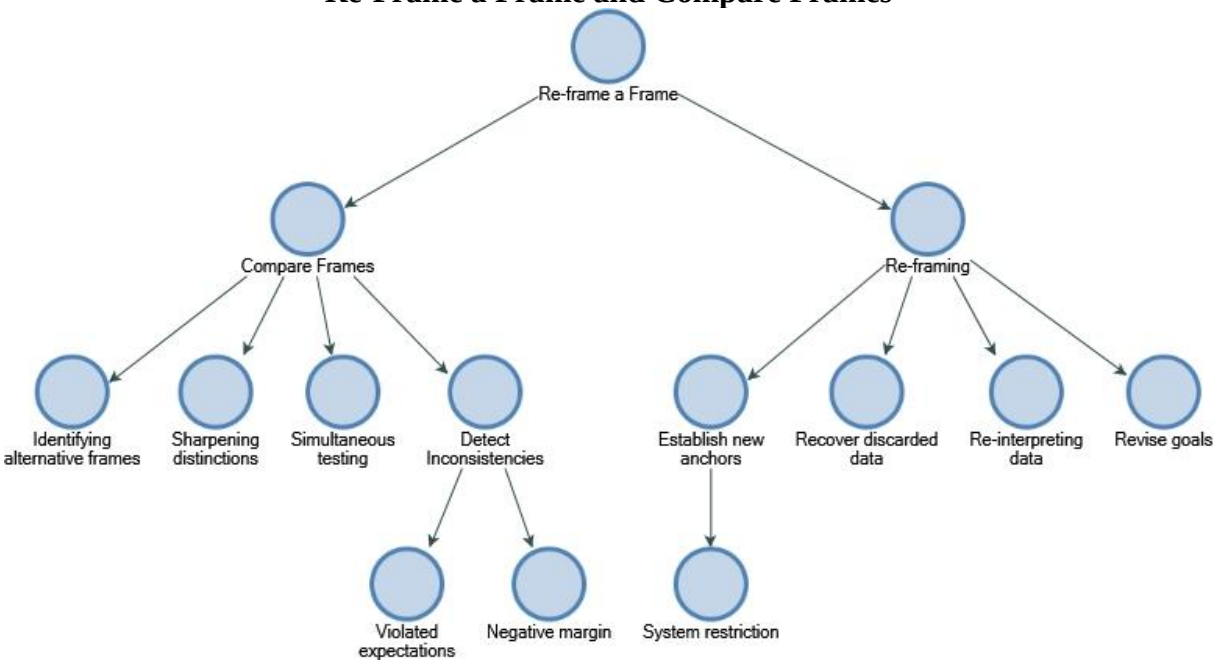
Elaborating the Frame



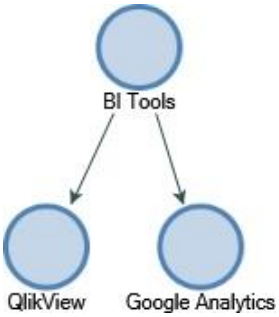
Question a Frame



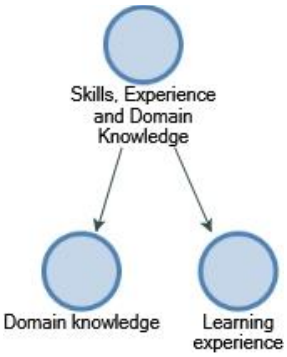
Re-Frame a Frame and Compare Frames



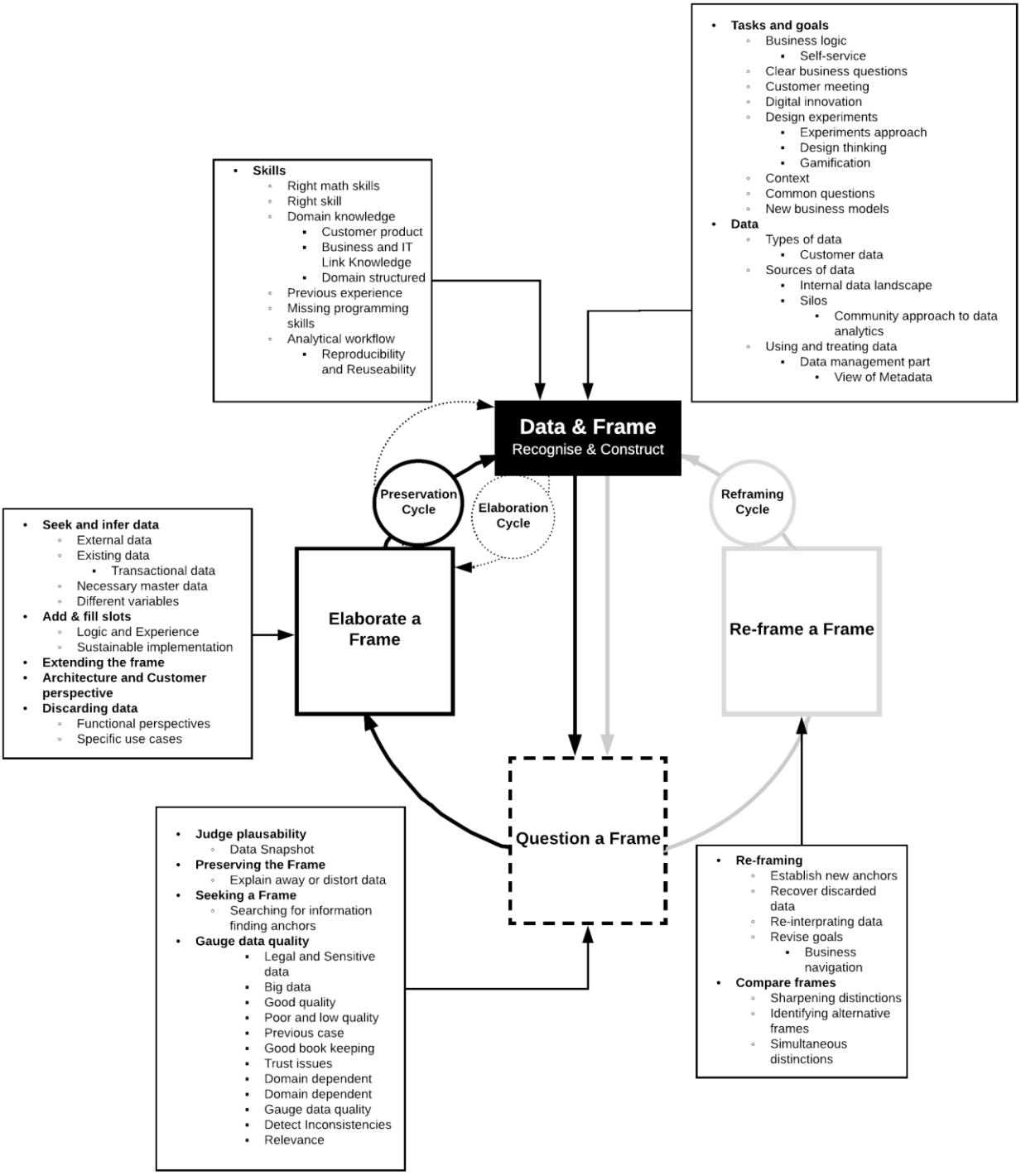
BI-Tools



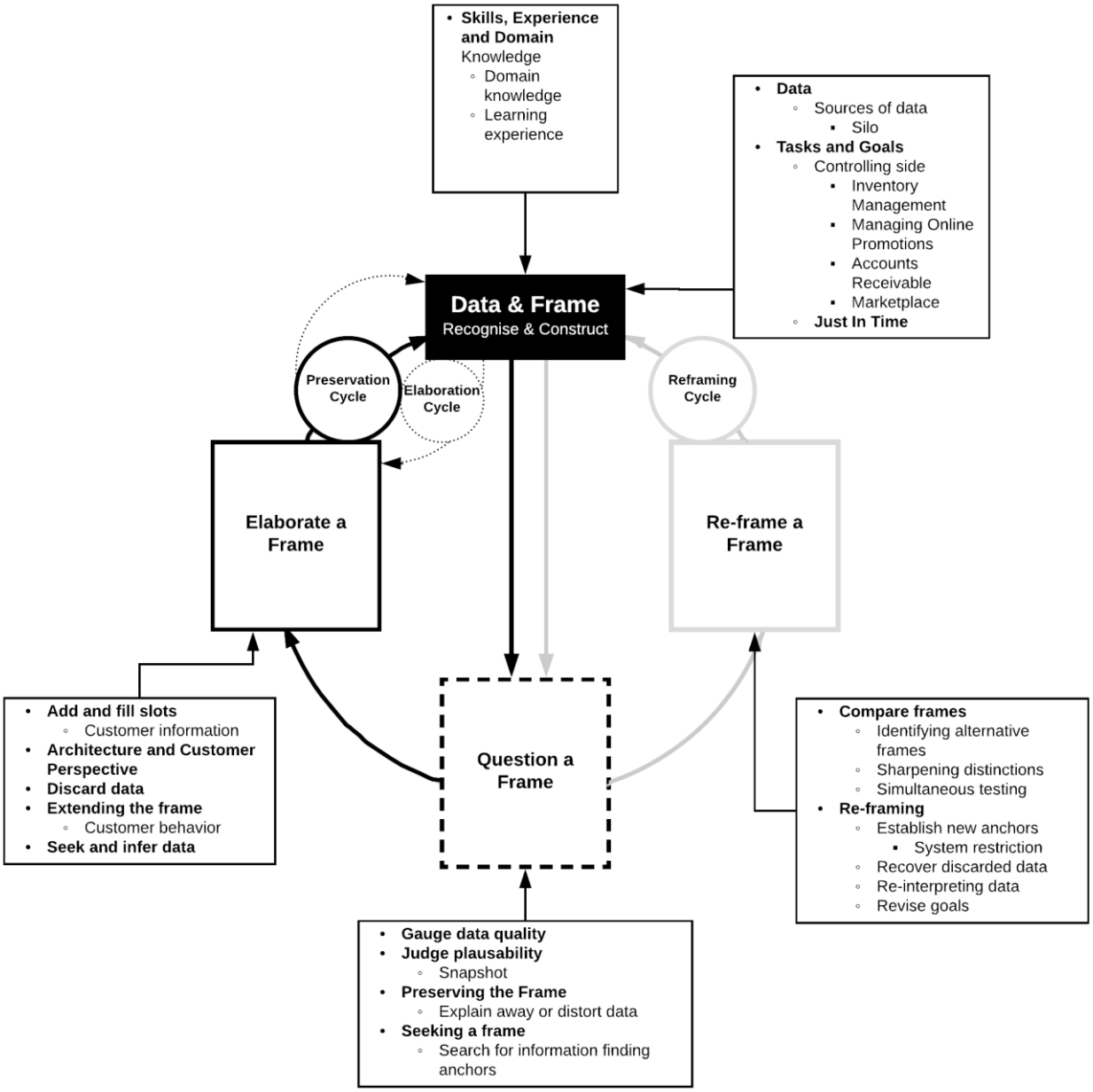
Skills, Experience and Domain Knowledge



Appendix 9 Data-Frame-Theory of SenseMaking in BI-Context IKEA



Appendix 10 Data-Frame-Theory of SenseMaking in BI-Context CDON



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