TRANSITIONING BUSINESS INTELLIGENCE FROM REACTIVE TO PROACTIVE DECISION-MAKING SYSTEMS

A QUALITATIVE USABILITY STUDY BASED ON TECHNOLOGY ACCEPTANCE MODEL

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Abstract

Nowadays companies are in a dynamic environment leading to competition in finding new revenue streams to strengthen their positions in their markets by using new technologies to provide capabilities to organize resources whilst taking into account changes that can occur in their environment. Therefore, decision making is inevitable to combat uncertainties where taking the optimal action by leveraging concepts and technologies that support decision making such as Business Intelligence (BI) tools and systems could determine a company's future. Companies can optimize their decision making with BI features like Data-Driven Alerts that sends messages when fluctuations occur within a supervised threshold that reflects the state of business operations. The purpose of this research was to conduct an empirical study on how Swedish companies and enterprises located in different industries apply BI tools and with Data-driven Alerts features for decision making whereby we further studied the characteristics of Data-driven Alerts in terms of usability from the perspectives of different industry professionals through the thematic lens of the Technology acceptance model (TAM) in a qualitative approach. We conducted interviews with professionals from diverse organizations where we applied the Thematic Coding technique on empirical results for further analysis. We found out that by allowing possibilities for users to analyze data in their own preferences for decisions, it will provide managers and leaders with sufficient information needed to empower strategic and tactical decision-making. Despite the emergence of state-of-the-art predictive analytics technologies such as Machine Learning and AI, the literature clearly states that these processes are technical and complex to be comprehended by the decision maker. At the end of the day, prescriptive analytics will end up providing descriptive options being presented to the end user as we move towards automated decision making. This we see as an opportunity for reporting tools and data-driven alerts to be in contemporary symbiotic relationship with advanced analytics in decision making contexts to improve its outcome, quality and user friendliness.

Keywords: Business Intelligence, Decision support, Decision making, Data-Driven Alerts, TAM, Descriptive analytics, Predictive analytics.

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Jude Edem Abormegah

1. Introduction

In this chapter the research discipline will be introduced followed by a problem discussion, a research purpose and a question which altogether serves as a guide for the research process. At the concluding sections, the delimitations of this study will be summarized and presented.

Background

The development and introduction of new and digital technologies is increasing rapidly. Simultaneously the business world is becoming more and more uncertain, volatile and complex with unpredictable changes in both internal and external demands and needs. This has created new challenges and opportunities for companies. Whiles successful adoption of new technologies could lead to competitive advantage, failure of same could lead to a plethora of unfavorable consequences (Olszak 2014). Thus Chrechuk and Zabarankin (2018) claim that improved decision making processes and practices have never been more necessary and appropriate in today's business world. Consequently, this creates an accurate urge and quest for acquiring, implementing and adopting new, dynamic and favorable digital capabilities, tools and software (Grechuk and Zabarankin 2018) as a means to ensure accurate and beneficial decision making processes (Mithas et al. 2013). In effect leading to the realization of a more flexible and improved business performance (Teece et al. 1997).

In this regard, Business Intelligence (BI) is a research discipline that can be described as an umbrella term that includes different concepts, methodologies, technologies and computerized systems (i.e. tools and software) which support and facilitate improved decision making-processes (Power 2008). In addition, Shollo and Kautz (2010) takes a wider approach and describes BI as a foundation of applications that enable organizations to make faster and better decisions by collecting and processing data into useful information as a means to ultimately enhance business performance (Boyton et al. 2015; Mithas al. 2013). In practice, BI tools or software have capabilities that can facilitate numerous use cases. However, common use cases refer to providing analytics, insights, values, reports and Key Performance Indicators (KPI) related to business processes and activities (Chaudhuri et al. 2011). In addition, Power (2008) clarifies that KPIs can be described as numeric index, figures, and values. These figures and values are oftentimes displayed graphically in the format of tables, diagrams, charts and bars. Additionally, these values can be accessed through BI-related dashboards which essentially are based on sets of KPIs that summarizes and presents the status and performance of activities and processes interactively (Power 2008). Today, BI tools and software can automatically send notifications or reminders to users based on KPIs whilst simultaneously enabling and equipping users with predefined sets of business activity related actions and recommendations (Power, 2008). It is however important to point out that there are no universal research definitions for these types of features. However, in the praxis field these are often referred to as data-driven alerts (Tableau 2020) or data alerts (Power BI 2020). According to these market leading BI suppliers, these features and functionalities enable users to be notified when a certain limit or threshold is reached in the KPI dashboards and is furthermore facilitated by real-time streaming of aggregated data (Tableau 2020; Power BI 2020).

Problem Discussion

During recent years, new and advanced BI tools focusing on decision-making support have been developed and are currently available to organizations (Boyton et al. 2015). Despite this, companies tend to be skeptical and hesitate to fully deploy and adopt new BI tools regardless of the increasing competitiveness, volatility and uncertainty in the marketplace (Canakoglu et al. 2018).

This is problematic as the research domain focusing on data-driven alerts appears to be relatively immature and limited. Simultaneously the new BI tools and software in the context of data-driven alerts require companies to be more digitally data-driven on a broader scale than previous BI tools and technologies in order to be able to fully harness the plethora of benefits that are highlighted by both BI vendors and research (Hussein and Poloczek 2018; Tunowski 2015). In parallel, Canakoglu et al. (2018) states that many organizations are facing poor or unsuccessful implementation and adoption rates of BI tools. This results in yet another critical challenge where users such as leaders, managers and employees may dislike, avoid and thus disregard data-driven insights and suggested actions derived from BI tools and software which consequently poses further difficulties for the adoption and application of new powerful BI tools and software in these companies (Hussein and Poloczek 2018). On this same topic, there is a challenge raised by the target market that current BI tools and software do not deliver upon their promise of providing or suggesting fast, reliable and accurate actions, notifications and recommendations that are necessary for companies' survival (Yang et al. 2011). Which is needed to fulfill the critical analytical requirements of a fast-moving and dynamic business environment where business needs and demands can change instantaneously and unexpectedly (Cronholm et al. 2017). Implications may lead to users underestimating the efficacy of Data Driven Alerts which will adversely affect its adoption (Yang et al. 2011). Additionally, Bach et al. (2016) declares that organizations are not likely to adopt BI tools, software or features particularly for decision making if they do not consider it to be both useful and effortless. This is oftentimes described as perceived usefulness and ease-of-use in the Technology Acceptance Model (TAM) (Davis 1993) which is one of the most influential models of technology acceptance. According to TAM, the two aforementioned concepts ultimately determine if a tool, software, technology or system will be adopted and accepted by a user for actual usage (Lah et al. 2020).

Problem Statement

In summary, only a limited set of peer-reviewed articles and publications related to BI in the context of data-driven alerts have been identified. Based on this literature study, it appears that the research domain is quite limited or immature. Simultaneously there has been some challenges identified associated with the fact that BI tools and software related to data-driven alerts require companies to be more digitally data-driven in order to fully leverage the benefits that are advocated by both BI vendors and researchers. In order to fulfill that scenario, it is of essence to establish a confirmed understanding of it in practice in regards to how BI is viewed and applied in different companies as well as from the end-user's perspective. These have consequently influenced and culminated our judgement on the relevancy to investigate the following problem areas and challenges:

- The application of BI in the context of decision-making support systems and data-driven alerts.
- The usefulness and ease-of-use of data-driven alerts from the perspective and perception of leaders and managers.

Purpose & Research Question

The purpose of this study is first and foremost to investigate and ascertain the extent to which BI is applied in the context of decision-making support and data-driven alerts in Swedish companies in different industries and secondly to develop an in-depth understanding of the usefulness and ease-of-use of data-driven alerts from the perspective and perception of leaders and managers. This we endeavor to accomplish through empirical research as a means to complement the current research domain with potentially new insights and knowledge both for BI professionals and academicians in the research field of BI. Therefore, this research will have a descriptive focus of receiving and developing a better understanding of the research subject. Hence the research questions are as follows:

- How is BI related to decision-support systems and data-driven alerts currently applied at Swedish companies in different industries?

- How do practitioners perceive data-driven alerts as tool to enhance their decision-making process?
- How do leaders and managers perceive the usefulness and ease-of-use of BI related to decision-support systems and data-driven alerts?

Delimitations

This research is delimited to the study of BI in the context of decision-support systems and data-driven alerts at private Swedish companies. Further delimitations comprise of the perception and perspective of leaders, managers and related professions in respective companies. As previously mentioned, BI is a broad term which includes different concepts, meanings and other related theories that can be applied to enhance a better understanding of the terminology. Hence for this study, BI will mostly be centered on the Shollo and Kautz (2010) proposed definition and explanation of BI and other related literature presented in the following *Literature review* chapter where our major concern is with the usage and application of the technology and not the technical details and software architecture. This could however mean that other theories and literature which may nonetheless be considered relevant in the research field of BI may not have been included in this study. Furthermore, this study will not align or concern itself with the implementation of tools from any particular BI vendor as that is out of scope with our research purposes which instead involves accuracy in collecting and analyzing qualitative data. The aim of the research however is to depict a general view to enhance the understanding of BI as technology in relation to the research purpose and its questions.

2. Literature Review

In this chapter we explore several literatures that are essential to better understand this research and its fundamental parts that are being discussed to set the context for this study. Our main purpose will be to describe a general background of the research subject and set the stage for the following chapter of “Theoretical framework” where among other things *Perceived usefulness* and *Ease-of-use* will be described in terms of how we have applied it in our research for collecting and analyzing the qualitative data. This chapter begins with a brief description of the decision-making process and its different approaches accordingly as described by the literature and is followed by the study of the environment that private enterprises operate. The latter part will describe Business Intelligence with regards to its definition, purpose, area of utilization and how it supports companies’ performance. Lastly, the chapter will explore how similar subjects to Data-Driven Alerts have been applied in other areas and in research.

Decision Making

One way of describing decision-making process is through *Simons model* which consists of three main phases: *Intelligent*, *design* and *choice*. The first phase, *intelligent* starts with the decision-maker (i.e. the one who is taking the decision and is responsible for its outcome) identifying a problem in the "real-world" e.g. operations environment and start the process of collecting data for an enriched understanding of the situation encountered. *The design phase* concerns constructing a model for managing the situation where different approaches of actions are developed. The last phase *choice* is where different solutions are compared by validation the outcome of each to select the optimal one for implementation to solve a problem (Turban 2015). Simon (1959) concludes that it is important efficient decision making processes to be embedded in an organization’s structure to facilitate and guide humans in taking the right decision to achieve a desired state. Thereby expressing decision making to be an essential activity to be performed by any organization in order to make any progress towards its set goals and objectives. Accordingly, decision-making consists of several specifications of steps needed to be taken within an optimal solution to address an issue. Along the same lines, it is further emphasized that the difficulties of taking decisions is due to the limitations in presented solutions imposed by *human rationality*. This is because a decision maker is a human being that has a limited cognitive capacity and capability in processing solutions within requisite time and therefore makes decisions based the on available information (Simon 1959). In accordance with Simon, Grechuk and Zabarankin (2018) relates decision-making to be associated with uncertainties characterized by the challenges of predicting the future. The author's approach for managing uncertainties is briefly explained by data that is being modeled and evaluated to minimize the risks of an outcome. At the end, a solution is chosen and therefore a decision is made (Grechuk and Zabarankin 2018). The model in their approach is a representation of the reality aimed for minimizing a decision error. The model needs to be anchored in the environment of decision making to receive the best outcome (Grechuk and Zabarankin 2018). The figure below visualizes the Grechuk and Zabarankin (2018) approach on how a decision is chosen during uncertainties based on available data to achieve a rational choice and arrive at the best possible outcome that is beneficial with no guarantee of a better outcome due to difficulties of predicting the future.

Figure 1: Decision making under uncertainties according to Grechuk and Zabarankin (2018)

Simon (1959) argues that decisions that are based on objective measure are actually influenced by the subjective grounds of the decision maker's perceptions of his own world, this indicates that the different views the decision maker has is only a fraction of the actual truth. This further suggests that missing details of events occurring further affects a person's inference and perception e.g. own cognitive mental picture of an action. Which Cronholm et al. (2017, p.6) define with the followed statement: *"Consequently, all these factors contribute to insufficient information for decision-making and sub-optimization due to incomplete sub-sets of data"*. Hence, despite how the decision is being made, there will be no guarantee of reaching the enterprise's desired goals and targets e.g. suboptimal decisions. Therefore, this requires effort from an organizational perspective of managing conflicting problems with other factors e.g. goals, policies etc. which are taken into consideration by different stakeholders when a solution is being selected i.e. decision making. In other words decision making can be considered to be about managing problems at a broader scale compared to solving a problem (Alkhafaji 2011), indicating that decision making requires effort and attention from the organizational perspective.

Types of Decisions

According to Schmidt and Wilhelm (2000) decision making from organizational perspective can be categorized into three levels: operational, tactical and strategic. Considering from a time perspective, strategic decision concerns an organization's utilization of resources to combat future uncertainty that may occur in two to five years based on different factors e.g. political landscape. Similarly, Alkhafaji (2011) considered strategic decision to be integrated with an organizations strategic planning of its future objectives and attentiveness for combating uncertainties. In most literature, senior managers in top management positions are considered to be the ones who take the strategic decisions that has major long term impacts influencing an organization's operations and business processes (Kulkarni et al. 2017). Tactical decision has shorter time span which most often than not concerns events that could occur 6-24 months ahead. An example of a tactical decision could be material flow in a manufacturing organization. Operational decision concerns events that occur weekly or daily within operations e.g. manufacturing activities where decision is being based on experience. (Schmidt and Wilhelm 2000).

Dynamic Environment

According to Alkhafaji (2011), the conventional statement is that profit driven enterprises and companies are operating in dynamic environments creating an urge for adapting to new changes and trends in order to stay relevant and active. Briefly explained, the characteristics of a dynamic environment consist of changes from different factors and stakeholders e.g. unexpected customer behavior, new laws, competitors etc. The underlining outcome according to the author is an increased competition among enterprises in similar industries creating a sense of hostility in the struggle for profit (Alkhafaji 2011). Teece et al. (1997) cautiously articulates the need of becoming aware of forces prowling in their domain in order to avoid threats or embrace opportunities for an increase steadiness in their position. The author emphasizes the importance of strategies i.e. acts of decision and its future consequences for avoiding or embracing changes in their environment.

Teece et al. (1997) states the term *dynamic capabilities* which enables enterprises to create new revenue sources essential for an enterprise's survival. The foremost benefit according to the author is having flexible organizational structures in adapting to changes where management has a crucial role to play. This according to Olszak (2014) is based on *resource based view* which in same manner describes an enterprise's ability of reorganizing and using their resources to execute a certain activity. Whereby reorganizing resources from enterprise perspective means transforming from one condition to another by combining different and available assets such as skills, knowledge etc. which can be achieved by implementing and using certain technologies. Mithas et al. (2013) confirms that technologies enables enterprises to increase their competitiveness, hence it is paramount that businesses combine *corporate* and *digital strategies* of implementing technologies to receive the benefits from embracing changes. In the same manner Cai and Yang (2014) stresses that enterprises will reorganize their resources in different ways depending on the environment and industries in which they operate, likewise they will incorporate different technologies depending on their strategies.

Therefore mechanisms are needed to collect, process and share information externally and internally enabling companies to respond rapidly to emerged forces (Cai and Yang 2014). The primary goal of technologies in decision making context is to produce information suitable for use as a foundation to base the decisions on and avoid uncertainties. Therefore it should be seen as a vital asset where data from the company's operational environment and competitors is being collected and processed into information to ensure competitiveness with peers and continuous innovative (Alkhafaji 2011). Teece et al. (1997) explains innovation in dynamic environments to be a key success ingredient to become *first-movers* by providing new services and products that satisfies customers and their potential customer's needs in a shorter time span e.g. *time to market.*

Business Intelligence

Business Intelligence (BI) is a multifaceted concept and umbrella term that describes things such as: *application*, *technologies*, *tools* and *processes* for collecting and processing data for decision making (Shollo and Kautz 2010). The evolution of BI has been discussed for decades without any confirmation of its precursors where many literatures are indicating different times for its emergence. Olszak (2014) is one of authors that states that BI can be traced back to the early 1970s, where different systems i.e. *Management Information System (MIS)* and *Decision Support System (DSS) were* being used to facilitate managerial decision making. The author further elaborates from an organizational perspective of how BI should be perceived as a means of assistance in all the three types of decisions. For instance, regarding strategic decision, information is needed to align an enterprise's path with its future objectives. For tactical decision, BI provides basic and in-depth information over an organization's departments and business processes e.g. sales, finance etc. For operational decision, BI enables *ad hoc* analysis instantly (Olszak 2014). Others define BI as *Information Management* used to provide useful information from different data sources i.e. databases, structure the information for its designated use in decision making by processing and enhancing parts of the information to suit the situation and the managerial level involved (Pirttimaki 2007).

From an Information Technology (IT) perspective, BI provides necessary and rich information for aiding the decision maker in acting towards an issue. Other IT-systems such as *Enterprise Resource Planning (ERP)* systems are mainly used for operational purposes within a company for maintaining efficiency in business process alignment with the business model to ensure production and provision of high-quality services and products with minimal effort. The difference between BI and other IT-systems from a technological standpoint is the *use of knowledge* from *information* as a basis for future actions (Kulkarni et al. 2017). According to Pirttimaki (2007), the outcome of BI should be the refined information and knowledge about a company's performance and the status of its business processes internally and externally. This could be described as *Sensing capabilities* in connection with Dynamic capabilities enabling a company to scan its environment for threats and opportunities as well as insights of its own strength and weakness (Baars et al. 2014). However, during the last decade the definitions have mainly focused on: *BI as a process*, *BI as a product* and *BI as a technology* e.g. software tools (Shollo and Kautz 2010). We will further explain BI in more depth considering these three parts to grasp a better understanding and comprehend the later parts of this study. For simplicity reasons we will ascribe to the Shollo and Kautz (2010) definition of *BI technology* as software tools employed in different use cases for analyzing data.

Business Intelligence as a Process

BI as a process refers to how we visualize data processing and its associated activities as illustrated by figure 2. Shollo and Kautz (2010) explains that the process initially begins with data being gathered and stored. *Data* is created through *business rules* in different IT-systems through *logic which* indicates the transactions that occur in relation to a database i.e. values in table rows. For instance a sales field in a table whose value is being manipulated through insertion, updating or deletion (Watson 2009). At this stage the format of the data according to the author is either structured or unstructured depending on its source. Shollo and Kautz (2010) explain that to process the data into *information*, it needs to be analyzed. In a nutshell, the activities that occur involve analyzing *organizing*, *filtering* and *aggregating* data into *information* through certain techniques and technologies whereby the data is placed in a context and is comprehensible to a human. From a practical standpoint the authors indicate that different quantitative measures are applied to transform numeric data into information. Humans can then mentally and cognitively interpret the information leading to the acquisition of *knowledge*. From the acquired knowledge, useful insights could be gained which could be beneficial for *decisions* through the enhancement of judgement about an issue. The knowledge is applied in a practical sense to make a choice in an organizational context to process an *action* for the target issue (Shollo and Kautz 2010). As previously mentioned, certain technologies and tools are used to facilitate each step of the process to obtain high quality outcome for effective decision making.

Figure 2: Illustration based on Shollo and Kautz (2010) description of Business Intelligence as a process

This refers to *Data-Driven Decisions* where a large set of data referred to as *hard data* is processed into information and then used as foundation for decision making to avoid making decisions based on assumptions and intuitions (Tunowski 2015). The data can be collected from a myriad of locations according to Watson (2009), the main data sources being retrieved from the company's core systems for operational use such as *ERP systems* as well as other external sources e.g. *web data*, *sensor data* from RFID tags and third-party data sources. However the majority of data analyzed is usually located in a *Data warehouse* (DW), a central data repository or database where data is structured and organized to facilitate extraction for data analysis (Ramakrishnan et al. 2012). The process that occurs between data sources and DW is referred to *Extract-Transform-Load* (ETL). Where data is extracted from source systems, transformed to a correct structure and then loaded into the DW (Watson 2009). Watson explains that this is often executed by a commercial tool or manually through queries e.g. *Structured Query Language* (SQL), a programming language widely used for the administration of relational databases. Time frame for uploading data into DW is often called *Load Window* where time interval for uploading and amount of data is regulated. From the process perspective, the data is aimed at increasing the quality of decision by reducing time for transforming data into information (Chang et al. 2014).

The quality of decision is determined by the quality of the data which according to Watson (2009) can lead to poor prediction and accuracy in analysis. Poor detailing from the data such as missing or incorrect values from data sources affect the accuracy of analysis and this is due to the fact of inadequate administration. These issues need to recognized and prioritized in an organization according to the author. In the same line, Butcher et al. (2009) advocates the need of incorporating other sources and web services i.e. cloud services integrated into DW to help improve data quality. In practical terms this means tools that could *clean the data* by detecting and removing errors and anomalies within the ETL-process. It is also expedient to have other sources that could be utilized for look-ups and data enrichment to help reduce the impact of missing data on the analysis.

Another challenge of BI in decision making is the time latency for when a decision is the most optimal one and has the most benefits with regards to the outcome. According to Tunowski (2015), the earlier a decision is made the more value in terms of benefits it is expected to receive. Therefore, the process needs to be accelerated to enhance proactivity. The author suggests *real time data i.e.* data that is collected in time, stored and processed into the DW under a short time span to improve the impact of data analysis and produce information at an instance for decision making. Tunowski emphasizes the pressure on a company's technological infrastructure to achieve this type of scenario. However if a company is able to effectively reduce time on data collection and prioritize data analysis, the value would increase according to the author (Tunowski 2015). Figure 3 below visualizes Tunowski's explanation of latency in decision making where in essence the figure illustrates business value versus time, the earlier an action is taken when an event occurs, the more value the action is expected to produce e.g. *action time* or *action distance*. At the same time the figure presents the meaning of real time data. Hence as previously mentioned, data quality should not be underestimated due to this result. Consequently, Ramakrishnan et al. (2012) mediates a sense of *nudge* i.e. reminder of consistency among its data collection where the quality of the data itself receives value in decision making. Meaning that collecting correct and purposeful facts and figures is important. Which Hadder et al. (2016) agrees with and further proposes that these tasks should be automatically executed with services for managing data collection and consistency.

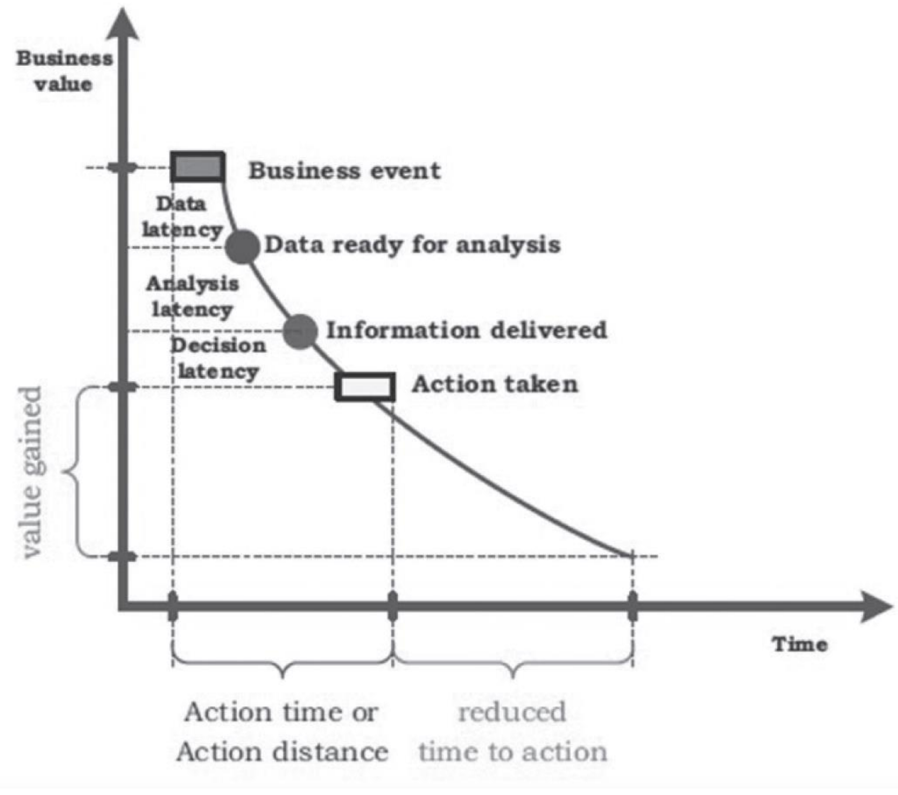

Figure 3: Latency in decision making (Tunowski 2015, p. 137)

Business Intelligence as a Tool

As previously mentioned, software tools and technologies are considered to be an integral support in decision making (Shollo and Kautz 2010). However in more detail, the capabilities that BI tools enable is inter alia: *data analysis*, *reporting* and *querying* where data is processed into information by applying different measurements and variables to make it comprehendible and interpretable by humans (Grublješič and Jaklič 2015). Moreover, the benefits of investing in BI tools is an increase in the value of the so-called *Return on Investment* (ROI) due to its impacts on business performance. ROI is depicted as the business value that stems from an investment which can be quantified in economic and financial measures such as cost reduction due to its ability of forecasting or reducing manual reporting of values (Boyton et al. 2015). The author further proposes that an investment in these tools should be derived from the needs of utilization of data as well as end-user involvement to ensure its successful implementation. According to Butcher et al. (2009) these tools which deliver the mentioned capabilities are called *Front-end BI services* as they are tools that users can interact with and are visually oriented.

Previous BI tools were mainly focused on utilizing structured data extracted from DW for analysis. Those utility tools were acquired and integrated into the organizational infrastructure i.e. in-house (Watson 2009). Shollo and Kautz (2010) prefer to call this *traditional* or *operational BI* where the focus of these tools were technically-oriented focusing on the functionality rather than its utilization for the intended need and purpose which the authors point out resulted decreased rate of deriving benefits from in its capabilities. Boyton et al. (Boyton et al. 2015) declares that a successful BI tool should at least have the possibility for the user to utilize an organization's DW in a standardized and simple manner as well as being able to utilize further data sources to extend and enhance their data analysis and align the organizational needs of delivering intuitive reports. This according to Shollo and Kautz (2010) is difficult to achieve with a traditional BI implementation hence within the last decade, different tools have emerged to help improve the rate at which organizations quickly achieve benefits from the capabilities of these tools.

Some of these BI tools have been packaged as web services or Software as a Service (SaaS) allowing users to access and utilize tools through the internet at subscription fee (Daas et al. 2013). The purpose of SaaS according to the authors is to enhance customer satisfaction through the value in the customizability that the user receives as they are provided with options in conformity with the preferences that they perceive useful for performing analytical tasks. Another benefit of BI-based SaaS is the price efficiency which is appropriate in accordance with its customer value as compared to the utility value because as more tools are being utilized over time, the higher the ROI will be (Daas et al. 2013). Self-Service BI (SSBI) tools are another emerging trend developed for providing simple and powerful analysis. The term Self-service in BI context points out regular business users i.e. analysts or managers without any deeper experience in statistics being able to analyze and visualize data to produce information without any reliance on support and developers from the IT-department i.e. IT-developers, *information workers* who on the other hand have years of experience in this field. Baars et al. (2014) depict SSBI to be more user-driven as well as data and analytically oriented due to the possibilities and capabilities of extensive analysis and scalability it provides by including and attaching other data sources to the analysis to enrich the explanation of certain phenomenon from large datasets. According to the authors, this can be achieved in these tools through exploration and drilling down of the data for details by emphasizing on certain data objects in a database.

Business Intelligence as a Product

The product of BI is presented through the outcome of the analysis which contains inter alia certain changes that occurs in company's environment i.e. customer behavior etc. (Jourdan et al. 2008). According to Chang et al. (2014), the approach for developing products could be through *reports, charts, Key performance indicators* (KPI), *dashboards* or *Online Analytical process* (OLAP) cubes. Watson (2009) describes further by stating that depending on user profession, different users or consumers of information will use different products. For instance, a manager from a strategic level could consume quantitative information from reports containing graphs and charts about certain issue of interest. Those who provide and consume their own information e.g. analyst could for instance use OLAP cubes allowing them to use their own queries for extracting information and view the data from different perspectives i.e. multidimensional as well as viewing the data in detail i.e. drill down (Watson 2009). With SSBI, Haddar et al. (2016) explain that it empowers users with simple *drag-and-*

drop functionality to enable them easily produce their own reports with information objects e.g. graphs. This features according authors removes the boundaries between user and provider of information by giving the user freedom of choosing which data should be included in an analysis form the data sources and how the end results should be visualized.

Others also prefer their information visualized through a dashboard which gives a more graphic and generic view of a company's business processes and is used for monitoring and analyzing numbers by utilizing graphs to easily reveal the performance of company activities. Dashboards and their layouts are customized depending on the users profession where the layouts will present different information (Kintz 2012). The author also mentions that some dashboards can be interactive through certain figures in the graphs to display further information by providing gestures during interaction. Another explanation of dashboard according to Watson (2009) is referred to as scorecards with summarized information about key activities within an company for instance amount of sales. The summarized information is often called KPI in among BI community. Haddar et al. (2016) defines KPI as measurements of aggregation functions i.e. *average*, *median* etc. containing an overview of either deterioration or progress in a business activity as well its performance as used to determine the success rate e.g. sales activity. Butcher (2009) explains that dashboard together with KPI functions are mainly for operational situations to present information on performances from various business activities and processes. Therefore, the author argues that information garnered is not optimal for tactical or strategic decision-making activities due to historical nature of the information whereby it is only representing *experiences* from what has been learnt in the past. This situation follows-through these KPIs hence one must analyze its impact and consequences in drawing lessons from it rather than it being in the forefront of predicting the future. Simultaneously the authors also emphasize their importance in companies by providing them with the ability to controlling operational activities, by monitoring results from business processes to achieve effectiveness e.g. cost optimization.

Descriptive, Predictive and Prescriptive Analytics

The area of BI with its components, definitions and use cases have evolved due to technological advancement. This has led to discussions about Business Analytics (BA) and value creation for companies and organizations. Where BA according to Lepenioti et al. (2020) is about utilizing data in a broader scale by providing further and deeper insight applicable for decisions compared to traditional or operational BI which primarily focuses on historical data i.e. past experiences, of an organization. Lepenioti et al. (2020) describe BA to be based on sophisticated measures of quantitative and statistical analysis applied for enriching the description of an organization's collected data to provide further and meaningful insights into an enterprise's performance and environments. Where the aim is to gain competitive advantage and therefore to enhance tactical and strategic decision referred to as *intelligence*. Furthermore, Lepenioti et al explain that BA can be divided into three categories depending on value and intelligence: Descriptive, Predictive and Prescriptive Analytics.

- Descriptive Analytics: refers to questions of "What" and "Why" indicating past or present events that either have occurred or is occurring in reference to real-time data in the context of performance.
- Predictive Analytics: tries to solve questions of future events that could or will occur in the words of "What" and "Why" by forecasting future trends or behaviors. Example could be predicting how much an enterprise's customer will consume at a future time.
- Prescriptive Analytics: In combination with predictive analytics explains what should be done and why, to achieve the predicted events. This also emphasizes along "What" and "Why" by referring to steps and approaches that needs to be taken to achieve the desired state of the prediction.

The following figure (see figure 4) visualizes the Lepenioti et al. (2020) explanation of the categories of analytics by presenting when in time each analytics promotes the most value gained versus when the least value is being lost. The *middle zone* between predictive and prescriptive analytics in the figure indicates proactive decisions and actions to be taken, providing the decision maker with suggestions or options which according to the authors could be automated whereby at the end reactive decision is implemented by returning to descriptive analytics. The authors state that current trend of analytics being prioritized in a competitive industry is descriptive and predictive analytics through technological methodologies such as *machine learning* (ML), *data mining* (DM) and *Artificial intelligence* (AI) which focuses on predictive analytics to enable us predict future events and patterns from large data sets by leveraging sophisticated computer and mathematical or statistical algorithms. Where at the end of a decision process, Lepenioti et al. explains that descriptive analytics can be applied in conjunction with prescriptive analytics to better understand the reasons for why an event occurred through diagnosis to determine the elements of the event to find the root cause of its existence. Afterwards, lessons and experiences can be learned in order to be more prepared for a similar event that could happen in the future or to be more proactive (Lepenioti et al. 2020).

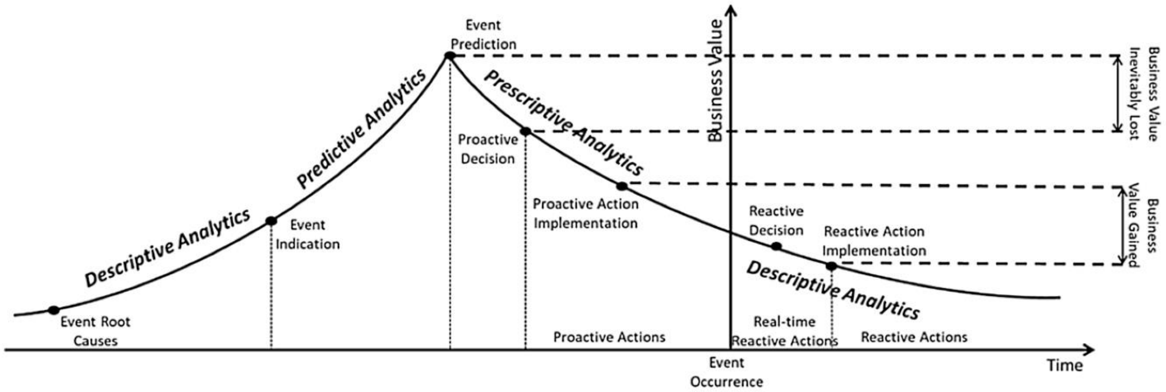

Figure 4: Analytics and its business value in time (Lepenioti et al. 2020, p. 58)

Chen et al. (2012) further explains what tools, techniques and products these different categories of analytics could include where descriptive analytics or *Decision support systems* according to the authors mainly focused on *reporting*, *monitoring* and *consuming* information from reports that included simple graphics and shallow figures i.e. graphs, as well as dashboards to analyze performance metrics where data for these products is extracted from operational databases and data warehouses. Since the expansion of the internet, the authors explain that data is now collected from the internet enabling different types of enterprises to become e-commerce because their operations and business activities now occur through the internet allowing customers to purchase items through websites leaving data of their consumer behavior. This presents a perfect use case for predictive analytics to analyze customer purchase history to get better and accurate insight through techniques such as *Artificial Neural Network (ANN), Pattern Recognition, Bayesian Networks* etc. The structure of the data in recent times now includes text and different data logs leading to an expansion of a company's data sources and management processes for unstructured data. The authors state that the enterprise's capacity regarding their technological infrastructure has now been increased to be able to store and manage data in different formats which is often referred as *Big Data* (Chen et al. 2012).

In addition to the above statements, Jaklic et al (2018) explain that predictive and prescriptive analytics provides sophisticated solution for complex problems which can be difficult to comprehend. This is possible due to its ability of conducting in-depth analysis to broaden its view of the details in decision making and hence may increase the value derived from utilizing predictive and prescriptive analytic techniques and technologies compared to descriptive analytics. Furthermore, Shmueli and Koppius (2011) explain the essence of the complexity behind predictive and prescriptive analytics by stating that it focuses on patterns and relationship in data set to find valuable insight which requires large amounts of data. This as previously mentioned concerns topics such as Big Data, enterprise infrastructure and complex computational techniques (Chen et al. 2012). However Shmueli and Koppius (2011) elaborates that all of these factors can be difficult to manage for enterprises at the beginning of a implementation phase due to resources and extensive planning as it requires new professionals and personnel that could manage the difficulties of interpreting these techniques and uncover casual explanation of events and are oftentimes referred to as *data scientists* in the field of IT. As previously mentioned, these processes are often complex and difficult to comprehend as it requires extensive knowledge (Jaklič et al. 2018) in other fields of IT e.g. programming as well as mathematics and statistics.

Previous Application Areas & Previous research related to Data-Driven Alerts

As previously mentioned, there is limited research about Data-Driven Alerts regarding its impact and adoption for decision making in academia. However, there is literature related to the subject where similar feature or functionality is utilized in other application areas for different purposes. Allali et al. (2019) have in their study investigated *Intelligent Transport Systems* (ITS) used for monitoring and tracking transportation services through dashboards. The study was focused on security of accessing these dashboards to understand its vulnerability using different notification services which enabled messages or notification to the user when an unauthorized user accesses their dashboard. The authors explained the alerts to be achieved through text messages or emails managed by a third-party agent such as a web service that provides these types of features. Allali et al. noticed that due to increase use of different mobile devices, an alerts feature of any kind will play an important role of mobility and flexibility where these devices can easily be notified of events allowing users to be proactive in taking actions (Allali et al. 2019). However, this study was not emphasizing proactivity in the context of decision making but instead of security and vulnerability basis for neutralizing threats.

Another study which focused on decision making from a medical perspective is Fletcher et al. (2017). They on the other hand investigated rapid response systems (RRS) in detecting signs from patients indicating severe symptoms critical for the patient’s health through a dashboard based on electronic medical records (EMR) data. The authors explain that this type of dashboard can support the medical practitioner’s decision making and work where alerts can have significant role by notifying the practitioner through different devices when a patient’s health is starting to deteriorate. On the other hand, the authors also indicate in their study that different practitioners could ignore these alerts if they consider these alert to be fatigue. As situation that arises if the algorithms for alerting the practitioners is not accurate leading to a so-called false alarm. This the authors explain can affect its usability and usefulness hence loss of trust in the systems. The accuracy and robust nature of these dashboards are extremely sensitive and could be improved by implementing features that enable the dashboard to manage rapid changes i.e. the data streams being processed and displayed (Fletcher et al. 2017). Ibrahim et al (2017) calls this type of feature *real-time reporting with analytical alerts* whereby there is efficient management of data streams of data that occur rapidly from different activities e.g. data acquisition, processing, preparation etc. Thereafter, when distributed into these dashboards will present an up-to-date information through KPIs, this is crucial for organizations requesting real-time data to avoid delays in reporting which can result in lost profits during transactions. Hence the authors emphasize in their study the importance of appropriate and sufficient network bandwidth allocation for applications and systems to increase capacity for managing the data streams efficiently. Furthermore, the authors also stress the outcome of increased bandwidth that it leads to efficient decisions due to instant information delivery. In the context of alerts in decision making, the authors present it as an essential capability for enabling organization to optimize decision-making when a critical change or fluctuation occurs in their business performance such as reaching a certain threshold in value through the settings as visualized by the KPIs. This once again can be achieved if the organization has the network and infrastructure capable to constantly manage data flows from different systems and applications which the authors refer to as bandwidth (Ibrahim et al. 2017).

3. Theoretical Framework

The following section will explain the background and motivation for the use of Technology Acceptance Model (TAM) as the thematic lens which has been applied qualitatively in this study to answer the research questions. The use of the theoretical framework enables us to grasp the investigated companies' user's perception of Data-Driven Alerts regarding its usability areas for decision making where the key concepts around the model are defined for collecting and analyzing our qualitive data. Therefore, literatures about BI and decision-making will not be explained in this chapter as was already achieved in the previous chapter. The Strength-Weakness-Opportunities-Threats (SWOT) model will be described and applied in the analysis section of this thesis as a complementary model i.e. chapter 6 – *Analysis*, for enhancing the description of Data-Driven Alerts usability. These two models will be used as a foundation for conducting our study in connection with data collection and analysis but with TAM being the primary model applied.

Usability – Introduction to Technology Acceptance Model

Usability can be defined from different standards or practice and contains a myriad of descriptions according to Holzinger et al. (2011). However, the common underlining definition that cuts across all standards and practices is the expression of efficiency and effectiveness of use to enforce positive reactions and state of being from the user i.e. user experience derived from utilizing certain devices or software (Lah et al. 2020). Briefly explained, efficiency describes the amount of resources needed to reach a desired performance whiles effectiveness aims to describe the outcome of a certain performance. From a technological stand point, Holzinger et al. (2011) describe usability as the quality of use derived from software tools aimed at satisfying the user's needs through its functionality in terms of the features required by the user to solve a specific problem. Furthermore, the authors also describe the essence of reliability of tools in their capacity and performance to support the functionality the user requests. Popovic (2017) explains that these guiding principles regarding usability should not be an exception when managing BI tools. This means the tool's features are an important matter in order to satisfy the user's needs and is related to the quality derived during its application in terms of interaction and utilization for a specific purpose.

As previously explained in the literature review, in order to succeed in a smooth transition and implementation of these tools, it necessary that the tools be aligned with the user's needs and organizational goals in order to integrate the technology into the organization's activities and tasks. (Boyton et al. 2015). This principle is often described as *adoption*, indicating the different stages involved with implementing a technology such as *accepting* and *integration*. Kulkarni et al. (2017) also states that adoption affects a whole organization at different levels where different activities need to be incorporated and interlaced with each other in relation to business process and tools. Where the person or the user behind these tools needs to feel a sense of ownership and inclusiveness. The authors explain that acceptance can only be accomplished if the features of the tool and the user's perception of derived benefits are aligned together. Once again in reference to the context of BI tools and their application for decision making, Bach et al. (2016) points out that the quality of information that these tools produce through different products i.e. reports can affect the satisfaction of the user. In the sense that these tools and its features should be perceive by the user to support decision making and hence consequently facilitate their work. Bach et al takes it further by stating that this could either affect the adoption of BI tools or its underlying features. Simultaneously, users in an organization must be encouraged to utilize these tools and its features in order to harness its capabilities to achieve better performance through the realization and understanding of how their skills in conjunction with the BI features will enhance and facilitate their work. Otherwise the users may be discouraged from utilizing the tools if they sense that the features are too stressful to utilize in comparison with their usual approach or are given a negative representation of the tool's capabilities or effectiveness which will inevitably lead to a rejection or underutilization of these tools. However the consequences are reflective both at the individual level as well as the managerial level which creates barriers preventing an organization from reaching its goals and objectives (Popovič 2017). In the case of BI and decision making as previously explained, if a tool does not satisfy a user's need for information there will be a decline in its utilization and use case leading to an outright exclusion from business processes since it does not provide useful insights necessary to be used as a foundation for decision-making.

Technology Acceptance Model (TAM)

TAM according to Bach et al (2016) originates from the *theory of reasoned action* (TRA) in the research field of *Information Systems (IS)*. Briefly explained, the main essence of the theory is to study and understand the environment in which a technological system or device i.e. IT system is being introduced to a user in order to observe the interaction between humans and technology and to ascertain the human perception of it with regards to their thoughts and views (Bach et al. 2016). Chang et al. (2014) explains that TAM was developed in addition to TRA to enhance the explanation of user acceptance which is the subjective motives a user has in order to be encouraged to utilize a certain technology. This has been applied in previous studies to determine how successful a technology will be perceived among its users through the domain concepts of *perceived usefulness* (PU), *perceived ease-of-use* (EoU), *intention to use* and *actual use.* The concepts PU and EoU have been found to be the most influential for a successful adoption of a technology as well as a smooth transition (Bach et al. 2016).

These concepts can according to Bach et al (2016) have a significant impact on the user's perception either about a feature or the entire system as a whole. Furthermore, the authors explain that it can be of great use for those who want to unravel the understanding of how a user views the interaction with technology in order to come up with advantages and disadvantages in context of its designed use case. Furthermore, the author explains that due to the model being based on TRA, the mentioned concepts is mainly anchored in psychology and cognitive factors which affect the user's perception of a technology in terms of its use case. At the same time, the author stresses generally that TAM is the most appropriate model or framework to apply in related-usability studies and has gained the most attention in the IS community in research where PU and EoU are the concepts that the majority of these studies have focused on.

Perceived usefulness + Ease-of-use = Actual use

Other authors indicate that TAM also focuses on the user's trust in a technology thus what encourages them into using it where the usability of a technology is centralized throughout the evaluation of the domain concepts. The first domain concept i.e. PU, focuses on the perception of how well the technology improves the performance of a certain task, the second concept i.e. EoU describes how simple a technology is to use in terms of its features and the learning curve associated with its operation (Lah et al. 2020). With these two concepts in mind, Lah et al indicates that this could be applied to determine the successfulness of an IT-system once it has been implemented. It assumes that successfulness in this case is concerned with whether the designated user *actually* uses the system for its designed purpose or not. Davis (1993) who is considered to be one of the main researchers in the field of IS with extensive knowledge of applying and extending TAM in research confirms the previous explanation of TAM by adding the importance of user acceptance and its relationship to a system's design and its features (see figure 5, below). This according to Davis can be studied through the domain concepts that is presented in the author's research for evaluating a technology in the context of usability. According to the author the concepts PU and EoU are mainly focused on capturing the behavior of the user in terms of attitude which in itself affects either the continual usage or discourages the users from utilizing an IT-system. The model depicts the user acceptance as being initially affected by the feature of an IT-system which is assumed to be the functions and their use cases of the system. The initial effect on user acceptance according to Davis is to be based on the *System Design feature* which can be seen in figure 5. EoU according to Davis (1993) also has a direct effect on PU and shows that PU can also be determined by the effortless interactions with the system's design feature.

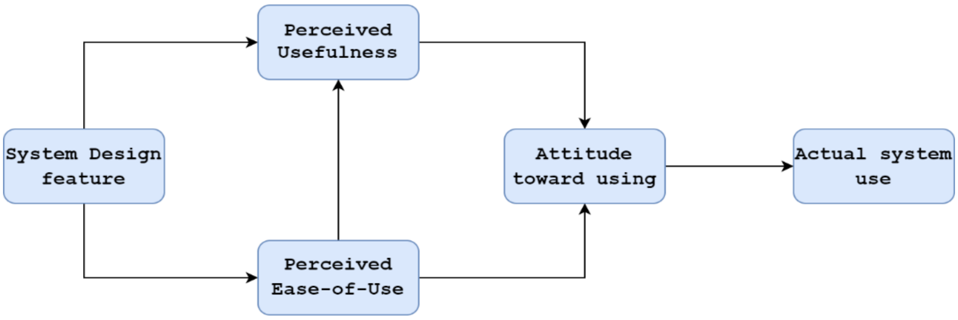

Figure 5: TAM and its concepts according to Davis (1993).

Bach et al. (2016) further states the possibility of applying TAM to study a BI tool's features and not only the tool itself. In this regard Bach et al. cites in their study other authors who investigated different OLAP techniques in order to bring out the user's perception of how well they perceived the various techniques' usefulness for analytical purposes and therefore adopting it for their use i.e. concept PU. Lah et al. (2020) presents a solution for how to apply TAM to examine a technology or product and its feature's usability areas in research, which table below presents. However, the author also stresses that this can also be used as an inspiration for other research methods in collecting data about usability from the user's perspective by using a qualitative research method. In the research field of BI, Jourdan et al. (2008) explained that different types of research strategies needs to be applied to increase the scope of knowledge about BI and to explore the fundamental areas of a subject area related to BI whereby using quantifying measures according to the authors can be difficult approach to study the context of BI tools in conjunction with decision making. Therefore, the model will be applied in a qualitative approach in order to ascertain the human aspects in relation to the technology being investigated.

Perceived Usefulness	Percieved Ease-of-Use	Intention to Use	Actual use
• Using [this feature] would facilitate to accomplish my work tasks • Using [this feature] would improve the job performance • Using [this feature] would improve effectiviness on the business activites	• Learning to operate [this feature] would be easy to comprehend. • The interaction with [the feature] would be understandable. • I would find [the feature] to considered flexible to use and interact with.	• I would considered to use [this feature] in a greater amount in the future.	• I would definitely use [this feature] more for its designed use case.

Table 1: Explanation of TAM and its concepts according to Lah et al (2020)

Strength, Weakness, Opportunities and Threats (SWOT)

The applicable use case of this model for analysis is applied as a systematic approach for forecasting factors that can influence the development and trajectory of an organization in regard to certain phenomenon such as competition, products, industries, political events etc. This is achieved by categorizing internal factors within an organization which are *strength* and *weakness* that an organization can control over and can adjust in comparison to external factors such as *opportunities* and *threats* that could occur in the environment where an organization operates and has minimal control over and often involves factors that could occur in the long term. These are often viewed in a four-field diagram visualizing the internal and external factors that affect an organization in a positive or negative manner (Nazarko et al. 2017). The authors explain that the purpose of using this model for analysis can be depicted as a complement for strategic decision making and planning in order to be prepared and adapt to future changes. The authors further propose that it is possible to apply this model to investigate and assess a technology that can be seen as a tool where the ambition is to understand how a technology achieves its goals and desired outcome in terms of performance.

Outlines from the Theoretical Framework(s)

In the proceeding sections, we will apply the Davis (1993) concepts of TAM i.e. *perceived usefulness* and *ease-of-use* as a qualitative foundation for collecting and analyzing the qualitative data obtained from various interviews where the concept *actual use* will be followed to complete the whole picture of the research . In other words, we will apply the TAM as a *qualitative thematic lens* to fulfill the aim of Informatics in investigating human perception and interaction with technologies. As Recker (2013, p. *v*) puts it, "*Information Systems [informatics] is the research field concentrating on the impact of information technology in use by individuals and organizations alike and is a fundamental element in understanding the current and future business, management, societal and individual practices"*. We will also draw inspiration from the Lah et al. (2020) proposed solution of how to apply TAM in research (table 1). Furthermore, this enables us to fulfil our research purpose and to answer our research questions by better understanding the phenomena of how BI is related to Data-Driven Alerts and Decision support and the reasons for the perception of the feature. The desirability of adopting Data-Driven Alerts to a greater extent for decision making among the investigated enterprises in our study will be done regarding to the concept or factor '*actual use'* in TAM. Therefore, this chapter compared to the literature review has given a description and defined the key concepts that will be used when collecting and analyzing the qualitative data. As previously explained, we will later apply the SWOT-model to assess the capabilities of Data-Driven Alerts in the context of decision making from a usability perspective in order to enhance the motivation of the research purpose. The aim of applying the framework(s) is to predict the future of BI tools that contain Data-Driven Alerting features and to see if it will be replaced by a new technology or feature.

4. Methodology

The following chapter will describe in detail the approach used and how the study was conducted with focus on the research method applied and the motivation behind it. Furthermore, this chapter will also describe the literature used for the study, the approach for conduction of interviews with the respondents and critical reflections about the applied approach regarding ethical considerations. The last part of the chapter will discuss the limitation about the research methodology and its appropriation.

Method Approach and Design

To conduct the study and be able to provide answers to the research questions, a qualitative approach was applied. The purpose of a qualitative approach is to collect data to give an in-depth explanation of a specific *phenomenon* in a given context described from different perspectives (Robson and McCartan 2016). Hence for this study, we endeavored to receive explanations from different groups of people in terms of their perception and their subjective views of BI and Data-Driven Alerts in different industries in order to understand what the respondent considers to be the trajectory of BI. Furthermore, a qualitative approach enables one to evaluate the reason of the desirability in a greater extent about adopting Data-Driven Alerts for decision making. In this regard, Data-Driven Alerts will be considered the *phenomenon* with the context being *decision making* as described by Robson and McCartan (2016). The authors proposed that this can be investigated by gaining rich and sufficient data through qualitative approaches such as *interviews* which we also consider to be appropriate and achievable for this study. As previously explained, decision making is a human activity in which different factors influence the human perception and its capability of taking decisions (Simon 1959). Recker (2013) also explains that by following a qualitative research approach, it enables the researcher to receive an in-depth explanation in comparison to a quantitative approach which rather focuses on statistical methods for gathering data from a larger population for objective answers. Hence, the latter is considered not appropriate for this research due to the nature of the study's research questions and purpose. To initiate the research and facilitate its proceeding steps in a qualitative regard, we followed a deductive approach. Recker (2013) describes that a deductive approach enables research based on previous theory and literature to draw guidelines for its study and provides an opportunity to anchor the study's empirical conclusion by basing it on previous research, this we also applied for initiating the research. Therefore, we began by gathering theoretical knowledge about the research subject from literature and previous research to help broaden our knowledge and understanding of the subject of interest. Thereafter, we endeavored to discover its connection with the empirical material we gathered from the respondents from the various interviews which will be discussed later in this chapter.

Furthermore, this study is of a descriptive character which Robson and McCartan (2016) explain as a means of observing how different groups and individuals view a subject in its natural form and the underlying reason behind it where the focus is on the past experiences of the factors. In this case, the descriptive character enables us to realize the real factors and explanations of the research subject to point out the indication of where BI as research discipline and as a concept in practice is moving towards in the near future based on the accounts of the actual users themselves i.e. the respondents. Where they are the ones who interact with these types of features and systems on a daily basis. A fact that Robson and McCartan (2016) confirms that receives a depiction of what the current state of being in regards to the subject of the research could be received by either a qualitative or a quantitative research method. Hence, we have followed the first mentioned research method due to the nature of this study. The opposite of descriptive study according to Short (2012) is a normative study which focuses on the confirmation of previous studies to come up with more accurate results and improvements in terms of establishing previous research and theories with the aim of detecting weaknesses. Which we will not try to achieve due to the existing and limited research about Data-

Driven Alerts. However, this is something that could be considered for a follow-up research in the future.

Pre-study: Literature Review & Theoretical framework(s)

To gain a deeper understanding of the research subject, we started reading literature about related topics for our research. The literature among other things included *decision making*, *types of decision, dynamic environment* and *BI* in general among others of which details were presented in the literature section (see chapter 2 – *Literature review)*. These literature and other materials where collected from *Google Scholar* and University of Borås database for journals *Primo.* The keywords used for collecting literature and journal articles were related to the research subject with examples such as: "*KPI alert*", "*Business Intelligence*", "*Business Intelligence*" *AND* "*Decision making*", "*Data-Driven Alerts*" *AND "Business Intelligence"* etc. To obtain high quality literature and journals among other materials, we filtered the search by applying specifications for *journal articles, peer-review* and in some cases latest publications. This quality control was instigated to enable us obtain high credibility in our study (Recker 2013). Due to this thesis being written in the field of *Informatics*, we processed and gathered information from the collected materials and articles which gave us general information about technologies by focusing our attention on the information relating to the benefits and use cases of certain technologies and techniques. Meaning, we processed the information from a user-oriented perspective instead of solely focusing on the technical aspects. During the literature review, we discovered that there was limited research about Data-Driven Alerts which may in one way or the other affect our study. Hence to compensate for shallow descriptions of the features and designed use cases from an academic perspective, we therefore focused and incorporated carefully curated similar subjects relating to Data-Driven Alerts which discussed the outcomes and use cases of similar features i.e. *EMR alert* etc.

When searching for a theoretical framework to grasp reasons of technology adoption from an organizational and user standpoint, one model that came to our mind of which we had previous knowledge of applying in previous studies was TAM. Therefore, we searched for how TAM had previously been applied in research relating to BI from different perspectives. As it can be seen from the theoretical framework section, we saw that other researchers have applied TAM as a thematic framework to study BI tools and its features which confirmed our choice of applying the model for this study however in this case quantitatively. Robson and McCartan (2016) explained that applying a theoretical framework is an essential tool used as a guideline for conducting interviews to collect the right and specific data in research. We facilitated our process of collecting data from the respondents and applied the theoretical framework for the analysis (see chapter *Appendix – Interview guide*) as *thematic lens* to grasp an understanding of the research subject. As previously mentioned, the topics and questions were inspired by the Lah et al (2020) proposed solution of applying TAM and previous literature review were also considered when developing topics within the interview guide. The motivation for using a complementary model such as SWOT was aimed at giving a better picture and explanation of the research subject.

Sampling of Respondents

The ambition of the study from the beginning was to focus on strategic decision making in specific industries especially large commerce, retail, and manufacturing enterprises in Sweden due to the vital resources expended and the experience gained from managing uncertainties (Schmidt and Wilhelm 2000) through BI tools and technologies for decision making. We sent out requests for participation in our study via email and through phone calls to specific respondents in the above-mentioned industries who we considered to be interesting for the research under a 4-week period. Our requests however did not garner the anticipated response where many could not participate due uncertainty in the state of affairs at the time (COVID-19 pandemic) or simply did not respond. Therefore, we decided to broaden up our scope of selection to other enterprises that were willing to participate by including Small-

Medium Enterprises (SMEs) and focused on the decision-making process by referring to the three types of decisions. The designation of SME refers to an enterprise or a company that has less than 250 employees (European Commission 2017). However, we considered this to have strengthened our study as it led to making our results and findings more significant due to facilitating similarities and differences between the investigated enterprises and companies in our research. Recker (2013) explained that in order to get valid data for the aimed research purpose and its question, the right respondents need to be selected for the study. Therefore, we relied on respondents that had expertise knowledge about the subject area by virtue of having acquired years of experience in either researching or practical knowledge who were also willing to participate. When we finally got in touch with potential respondents, we had some criteria that was inspired from the literature review that needed to be fulfilled to a certain degree which we discussed with the respondents prior to conducting the data collection activity. The criteria that we based our sampling of respondents on can be seen below in *bullet points*. However, it is worth noting that the tools in itself were not the focal point in this study and therefore were not included in the empirical section, section 5 – *Empirical result*.

- Familiarity with the terminology BI and has experience working with the latest versions (< 2 years) of any of these tools: Power BI, Qlik Sense/Qlik View, Tableau. These tools according to our knowledge have Data-Driven Alert features built-in.
- Familiarity with or have utilized Data-Driven Alert features in their work for decision making.
- Work experience in Manufacturing, Automotive, Retailer, Commerce, or similar industries where one of their offices is in Sweden. If not, then find representatives that either worked with these Swedish industries in research or in practice and has knowledge of their decision-making processes.
- Associated with work tasks that are related to decision making in their respective enterprise. Example could be supporting or providing information for decision makers.
- General awareness and knowledge of recent trends in the field of IT.

The following table (see table 2) represents the respondents we interviewed and the type of enterprises they represented (Representation) where the respondents Gamma and Beta have experience from working with large enterprises which will be explained later in the following chapters. Furthermore, we have assumed that if the respondent has worked with BI tools for a couple of years, then they are considered to have experience in the field of BI. This is implied for the respondent Delta, who is a business controller but have worked with BI tools in practice for a period of 5 years which is depicted in the table below. Some information was not relevant to include in the table e.g. Years of experience for the respondent Gamma which is marked with N/A (Not applicable).

Respondent	Profession	Representatives	Company size	Perspective & Position	Years of experience in BI and/or IT (years)	Duration of the interview in minutes (~)
Alpha	IT manager	Retail	SME	Tactical/Strategic	6	91
Beta	BI consultant	Commerce & Retail	Large	Strategic	10	83
Gamma	Researcher	Automotive & Manufacturing	Large	Strategic	N/A	33
Delta	Business Controller	Product Development & Ingredients	SME	Tactical/Strategic	5	27
Epsilon	Data Analyst	Warehouse & Distributions solutions	Large	Operational/Tactical	14	55
Total	**5**	**5**	**N/A**	**N/A**	**N/A**	**289**

Table 2: Information about the respondents

Data Collection: Semi-Structured Interviews

To collect data material for our study, we followed a *semi-structured* approach when conducting interviews. According to Robson and McCartan (2016), semi-structured interviews have a form of guidelines of topics that can be followed in conducting interviews to ensure collection of purposeful and appropriate data for the study. In other words, it is a quality control measure for increasing the validity of the study's results. Therefore, we applied TAM as thematic lens which included topics of the usability of Data-Driven Alerts in accordance to the domain concepts in the model. Also, Robson and McCartan (2016) indicates that a semi-structured approach in interviews allows the respondent freedom to elaborate answers leading to a much more richer understanding of the respondent's views and thoughts about certain topics. This approach also allowed for follow-up questions which seemed as an interesting opportunity to exploit. We conducted five interviews in total all remotely through telephone and online communication tools e.g. *Skype*, due to restrictions on physical meetings amidst the COVID-19 pandemic. Some of the interviews were conducted in Swedish as requested by the respondents. Before initiating each interview with respective respondents, we explained who we were, what our research subject was about, its purpose and requested to record the interview sessions to facilitate transcription of the interviews. We also explained to the respondent that collected material will be processed anonymously and confidentially (see *ethical considerations)* to enable safeguarding of respondents' identity (see (Recker 2013)) by renaming their names into Greek Alphabets (see table 2). Furthermore, to facilitate discussions with respondents in a cordial and seamless manner we forwarded to them the topics of the interview questions beforehand for their perusal and preparation. The reason behind this was to adequately prepare the respondents to provide answers that were considered meaningful for the scope of the study. Thereafter, we initiated the interview with introductory questions about their professions and progressed steadily to focus on the essential interview topics. With some of the respondents, we applied the *snowball* approach after the interview was conducted which Robson and McCartan (2016) explain as a process whereby respondents after having given enough information about a particular subject proceed to suggest other respondents for sampling and collection of more data. However, this approach yielded no positive results either taking into account other prevailing circumstances at the time.

Data Analysis – Thematic Coding

We were inspired by the Recker (2013) approach called *Thematic Coding* for analyzing qualitative data. Briefly explained, it is an approach for coding words or sentences of interest in connection to the implied theory in a study where sentences or words is a matter of subjective interest for the study to explain reasons behind a phenomena (Recker 2013). Our process of analyzing the collected material consists of 5 steps: *transcribing, reading, generalizing, coding* and *label placement.* First and foremost, we began by transcribing the recorded interviews in several document files which ended at about 23 transcribed pages in total. Those interviews that were conducted in Swedish were transcribed and translated to English for easy integration with the rest. Thereafter, we began reading through the collected material by reviewing the questions that have been asked during the interviews to obtain a better overview of the data. This enabled us to determine some information of which the respondents requested to be generalized. The third step included either the removal of some parts of the material considered to contain sensitive data or to rewrite parts of the information to be more abstract by excluding any identity revealing information. The intention here was to preserve the information that we considered to be important for the study through a general description. The fourth step was the coding activity as is it is the essential part of the analysis, where we read line-by-line throughout the transcribed document and labeled or marked sentences of interest in fewer words. In practice this meant that for each transcription that had been generalized, we coded sentences or words that encapsulates the respondent's expression of the research subject and the phenomena with one or fewer words that describes the essential meaning of their statement about the covered topics in the framework. Next was to highlight the sentences by labels which were then placed in themes or categories to give a richer description of the phenomena (Recker 2013) as a means of streamlining the codes into fewer themes to facilitate the next step in the analysis process. A practical example in our analysis, could be when respondents discussed "*poor information from alerts*" that had already been encoded, which we marked as *"low value".* The last step in the *label placement* was where all themes of the streamlined codes from each transcription was merged and placed in association to TAM and its concepts namely: *Perceived usefulness, Ease-of-use,* and *Actual use.* The last concept of TAM i.e. *actual use* was needed to unravel the final moment about a features' future and its existence in a respective company. An example of this was the previously mentioned label *"Low value"* which we placed in the category of *Perceived usefulness* based on the respondent's explanation and the theory description of the concept. It was during this step that we found a fourth category from interview when we applied TAM which is *Definition and perception of Data-Driven Alerts.* We determined this category to be of great use in our study and important for giving a richer and deeper understanding of the research subject and to solve the answer to one of the mentioned research questions. In summary the last step of the analysis *label placement* was where all of the themes from the *coding*-activity were placed in their overall categories which Robson and McCartan (2016) explained as a form of global theme in unification to one map that describes the outcome of a qualitative study. In this case the map consists of several maps anchored primarily on TAM and its domain concepts: *Perceived usefulness, Ease-of-use, Actual use* and *Definition and Perception of Data-Driven Alerts* where the first three categories are extracted explicitly from TAM. As previously mentioned, the last concept i.e. actual use was considered important as a form of presenting the respondent's final thoughts and views about the research subject. The last category i.e. *definition and perception of Data-Driven Alerts* was added in conjunction to the theoretical framework to enhance the understanding of the subject.

As previously mentioned, the interview guide for developing the interview questions and topics was TAM where the focus was mainly on perceived usefulness and ease-of-use. Therefore, when it came to the data analysis of our study, we constantly strived to take TAM into consideration even for thematic coding. However, some of respondents were speaking broadly around the concepts which could sometimes make it difficult for us to exactly place the coding and its labels in each domain of the framework. For quality assurance, the last step of the analysis process was where we solely focused on the domain concept as a means of validating the analyzed transcribed material with the description of TAM and its domain variables explained in the *Theoretical framework* chapter to fulfill a consistency with the topics covered in the interviews. The empiric result shows the outcome of the thematic coding where explanations were added to the themes and codes. The analysis section in the thesis presents more explicitly on the codes, marked in cursive which is depicted a few times in the *Empiric result.* Therefore, the gravity of TAM as our framework has facilitated our analysis of thematic coding by organizing the collected data in a distilled form. As previously explained, SWOT model was used as a complementary model depicted in the analysis section to emphasize on the use case of the feature whereby the model was developed lastly (figure 6) when the thematic coding was done. The connection to thematic coding and SWOT model is more of a general character to inform the reader of the content of the outcome from the data analysis and to enhance the understanding of the feature's usability. In its essence, the primarily framework was considered first in the data analysis and SWOT was later developed as soon when thematic coding was finished around the domain concepts. At the end of the analysis and thematic coding, we completed the research subject by putting it into perspective of previous literatures reviewed in the thesis i.e. *Literature review* which are depicted in the chapter *Discussion.* With the purpose of stepping back to discuss our findings from a more objective view of what the literatures points out to consider important from our findings in order to broaden our understanding and to fulfill what Robson and McCartan (2016) explain to be the essential purpose of qualitative studies which is to receive the so called in-depth explanation of a phenomena. This we strived to achieve by strengthening our findings from the literature perspective where we anchored the findings from the *Empiric result* and *Analysis* chapter in this thesis in a broader perspective in relations to the literatures.

Some of the steps were conducted iteratively to prevent overlooking or missing valuable data that could prove essential during the analysis (Robson and McCartan 2016). Furthermore, we considered this approach to be efficient and appropriate for our study to analyze the collected material due to the characteristics of our preferred framework. Meaning that the model took up different themes which we considered could be easily associated with the theory and literature in the previous sections to draw a general and broader conclusion based on literature review and theoretical framework.

Ethical Consideration

We strived during the execution of the study to collect material aimed for generating new knowledge in academia. Where our focus was to acquire knowledge meant for understanding the factors that influenced how professionals in different enterprises perceive decision support systems and data-driven alerts regarding its designed use case for decision-making and how it relates to its desirability of adoption. This we believe is relevant for other professionals that work in the domain of BI and other academicians. Recker (2013) describes that the purpose of research is to create insights which could be relevant for individuals and for society in general. Therefore we have during the course of our study not only taken into account ethical considerations of how our study should be of value to academia but also how it affects the respondents who participated in our study (Recker 2013). In every possible manner, we endeavored to achieve this by giving explanations to respondents before initiating each interview on the purpose of our study as well as how it will affect them and how the information given during the interview will be managed confidentially and anonymously to safeguard their identity and privacy. Lastly, we explained to the respondents that the materials collected during the interviews will only be used for this study.

Methodology Discussion

We have identified three factors that may pose some limitations and could influence the results of our study in terms of validity and reliability. Recker (2013) explains validity as how well the followed method captured the essential data for the research purpose and its questions whilst reliability concerns the consistency of reproducing the same results by applying the same research method. The factors are: *number of respondents*, *right respondent* and *mode of conducting interviews.*

From the beginning we had the intentions of interviewing several professionals from different industries. However, this was difficult to achieve due to global setbacks and challenges that affected Swedish industries and companies which was also far beyond our control. This could lead to the limitation of determining different professionals' perception of data-driven alerts from a few numbers of respondents. In other words, the result's significance in determining similarities and differences between different enterprises could be vague due to the fact that we were able to interview five persons from different industries. On the other hand, our results can still give a reasonable indication of how Swedish enterprises perceive data-driven alerts as well as adopting it at a greater scale for decision making.

The second factor relates to issues that influenced the sampling of respondents where availability and readiness of the respondent played a greater factor besides the respondent criteria that we had previously enumerated to guide our selections. This therefore led to other professionals from different industries being considered which although from the beginning of the study were not primary targets for data collection. This could be seen where some of the respondents are representatives for different industries due to having long work experience or researching within such industries. Consequently, this could lead to a dependency or relying on the respondent's view and answers on the subject instead of directly speaking with professionals working solely in these industries.

The third factor is that we only used one method for data collection i.e. semi-structured interview. Robson and McCartan (2016) explains that when conducting interviews there is a risk that the respondents may be affected by bias. In our case, this could mean that the respondents could have adjusted their answers and views after we presented our research subject to them. Furthermore, all the interviews were conducted remotely either through Skype or telephone call where there is a possibility that the respondents after viewing the topics for the interview may have structured their responses leading to superficial answers. Some of the respondents also had limited time which meant that the respondent had to adapt to the time available which made it difficult to ask follow-up questions or they not satisfactorily addressing follow-up questions rendering some responses not effective enough for use in analysis. An optimal scenario would be to complete interviews with another method for data collection e.g. observations, which according to Robson and McCartan (2016) would give a natural and richer view of the respondent's perception and therefore give further and meaningful data compared to conducting only interviews. This was not feasible to conduct with respective respondents due to time constraints as well as restrictions and limitations on physical meetings.

5. Empirical Result

In the following chapter, the processed material from the interviews will be presented and the compilation of the respondent's answer will be categorized according to the previously mentioned theoretical framework, TAM as our thematic lens. A fourth category has been identified and added in this chapter to facilitate the explanation of data-driven alerts due to the limited availability of research in this sphere. The four categories described are: *Definition and Perception of Data-Driven Alerts, Perceived usefulness, Ease-of-use* and *Actual use.* The processed material will be placed under its appropriate category based on the respondent's answer followed by a description of the views as previously explained in the methodology chapter where we processed the material using thematic coding.

Definition and Perception of Data-Driven Alerts

All the respondents from the interviews were not explicitly familiar with the terminology and its definition. Therefore, we initiated the interviews by discussing about Data-Driven Alerts in general and the respondent's perception of it before the discussion touched around the topics of the domain concepts that were previously explained. However, most of them knew the essential meaning of this type of feature due to having interacted with similar features in a practical sense during work related tasks or in research. Where they have heard similar terminology from their daily work aimed at describing the applications used in their organizations. Respondent Gamma explained abstractly what this type of feature is meant for and how it works:

"[….] describes when a system [BI-tools] tells someone something to consider [In KPI or in Dashboards] or to mark a change [….]" (Gamma).

Likewise, the respondent who works in an SME describes it as a type of "*Buzzword*", meaning that tools and techniques in the BI supplier market are constantly emerging and there is a constant discussion in the BI-community about these kind of features regarding how to adopt it into organizational strategy for better performance. Even though both of these respondents in their line of work within data analysis using different BI tools operationally on a daily basis for decision making or overseeing business performance have encountered similar types of features in these tools, they however used it for other purposes other than being *"alerted"* through email or mobile devices remotely.

"[…] another hype about it.. [….] where everyone [In BI and IT community] is talking about using it for better performance […] maybe it works [for decision making] …" (Delta).

Respondent Beta with several years of experience working with large enterprises in retail and commerce expressed that the feature is no longer current in these types of enterprises due to other emerging technologies such as *Machine Learning* and *AI,* where the focus of reporting and monitoring of business performance have led the focus of these technologies to predictions and forecasting:

"*Machine Learning and Analytics have matured […] where application use [of these technologies] has increased and getting more attention [from these types of enterprise] compared to Data-Driven Alerts [….]*" (Beta).

Gamma who has worked and done research on *Data-Driven Decisions, Data-driven organizations,* and *Innovation* using advanced analytics in large enterprises like manufacturing and automotive industries pointed out that at the end of the day despite the type of advance technological features implemented, the key is the organizational attitudinal change in adapting these features in order to gain benefits for improving performance. Indicating *the human-technology aspect*, where this must occur contemporarily for an organization to derive full benefits. Gamma in current and previous research has extensively investigated how to overcome such barriers regarding challenges of adopting technologies which enables organizations to become more data driven.

Perceived Usefulness

When it came to discussing one of the domain concepts from the theoretical framework which was the perceived usefulness of Data-Driven Alerts or similar features, the respondents in SME spoke from previous experiences with this type of feature and their interactions with tools that they are using for work on assignments. They expressed that due to interacting with KPIs and Dashboards on a daily basis where they monitored key values and their changes, there is no need for receiving a notification that a change has occurred in any of these KPIs. Both respondents work with *indications* in their dashboard that marks changes through color or a prompt message to draw attention when a pre-defined change has occurred and needs to be further analyzed or investigated. An example according to one of the respondents could be a *window message* that presents information when sales have dropped down to 20%. Epsilon who works with data visualization and creating dashboard for managers in their organization have found Data-driven Alerts and similar features to be useful for overseeing several of their operations and business activities that occurs at their operational level i.e. assembly line. Therefore, the respondent implied in practical terms that instead of manually monitoring operational dashboards where values of KPI have fluctuated below or above an unexpected threshold, the systems i.e. the tools tells the analyst of important issues that have occurred for a proper assessment of the situation to determine if human intervention is needed for managing the issue:

"*[….] In relation to the dashboards and alerts, the easiest way to indicate something is wrong is to color the background of say the count of messages in a message queue by coloring the background red if something is wrong, if there are too many unprocessed messages, and green if everything is ok. […] This can assist […] managers to plan works to be done days beforehand and optimally use employees that are needed"* (Epsilon).

The same respondent continues the discussion by also explaining that caution should be exercised when the tools indicate an alert or too many alerts to avoid overcommitment or misappropriation of resources that could be useful for other problematic areas:

"[…] if the data indicates wrong info there is a risk of committing too much resources for staffing […] when it comes to monitoring it can also be used to indicate when something is wrong with the system [itself] too much processing power […] too much memory used, too many messages in the message queue […] leading to unresponsiveness [dashboards] " (Epsilon).

Likewise Alpha stated that there are several flaws that could occur when interacting with these types of features. According to Alpha, one of them is that Dashboards and KPIs only gives an *overview* of *what is happening* or *what has happened* in their business processes. Where the information presented is shallow indicating difficulties of getting a deeper understanding of the reasons behind it. The following is the statement Alpha gave in accordance with this flaw:

"*The problem with dashboard and other things [the KPI associated] is that it only gives you an understanding of the past [historical data] and not exactly what has happened and why [….]*" (Alpha).

In accordance, Beta explained that the Data-Driven Alerts feature in reporting and BI tools can enable business executives and other users to minimize the time required for monitoring KPIs and Dashboards except for when a critical change is occurring. At the same time these types of uses according to the respondent does not give an executive or a decision maker adequate information to make powerful decisions required to achieve competitive advantage which is the primary goal that these organizations and enterprises are striving for. This further suggests that the information presents "past events" which can prevent enterprises in the commerce and retail space from becoming proactive in decision making.

"These [reporting tools] focus on historical data which describes what has happened in the past. Where other tools like Self-service BI enables a user to explore data further to see not only what has happened but also why" (Beta).

In conformity with the above statement, Epsilon in a similar expression explains that the alert these tools are sending out needs to be meaningful hence the data needs to be accurate to base an action on. Otherwise it will lead to misuse of resources and therefore could potentially lead to personnel having lower trust in these features which will subsequently lower the prioritization of these alerts. It is of importance according to the respondent to manage these issues correctly in a timely manner before it exacerbates to affect performance leading to a decrease in customer satisfaction.

Beta explains the usability of the features in a decision-making context where getting an "alert" will therefore not provide essential information for being proactive. Indicating a situation where the outcome will according to the respondent be either profitable or costly since these "alerts" or "messages" may not provide sufficient foundation for embracing or mitigating threats and opportunities in these enterprises. However, Beta also mentioned during the interview that there are useful applications for these features in KPIs and dashboards in general where it enables executives or managers keep track of the key numbers of their organizational performance and activities to ensure optimal trajectory to their goals and ambitions. Beta further describes therefore that new techniques and technologies such as *Machine Learning* when applied will play a bigger role in predictions and forecasting enabling enterprises to make better decision and allocating their resources better for achieving a desired outcome. Beta gave an illustration to how meaningful insights from new technologies with predictive capabilities are useful for decision making:

"*These new technologies [with predictive capabilities] are better at looking [for] connections or patterns than a human could achieve [….] so instead of being reactive, you become proactive at decision making and are more aware [….] example could be which customer are going to buy certain items […] which generates more value than using KPI* " (Beta).

From a larger enterprise's perspective in the automotive industry, Gamma in the same line as previous respondents mentioned that reporting i.e. KPIs are less data-driven than newly emerged predictive analytics which enables more and further insights than previously. From a decision-making standpoint, moving from intuition to data involves providing more trust in the latter. This according to the respondent could be difficult to achieve due to the difficulty relating to culture and behavioral change, something that the respondent explained requires great effort and time to achieve from previous experiences. At the same time, Gamma points out that these enterprises are aware of the derived value from predictive analytics in their work and decision:

"*[….] Simple statistical analysis [Bars and charts] with reporting tools [KPI and Dashboard] that shows present information doesn't give a value that these enterprises [automotive and manufacture] are striving for in order to remain competitive*" (Gamma).

Going back to the perspective of SMEs and discussing indications and their effectiveness for Alpha and Delta for their operations and tasks in their respective enterprises, Alpha shares the ambiguity of using indications for monitoring their operational activities and for decision making to formulate new objectives. The respondent in line with previous statements about the overview and shallow information further implied that the responsibility of exploring the reasons why certain key values are indicating in a different color is on the user behind the dashboard. Where different users may perceive the reasons in different ways hence, they must drill-down to gain a better understanding. Therefore, the respondent further expressed that this could lead to explaining why the information of the event is not being decentralized since the enterprise could lose valuable explanation for lost revenue in their operations. Delta however explained that in their organization different users and workers can access each other's dashboard depending on their task and profession. Hence, the difficulty of the indication in their case where the tool tells someone to consider a change in their operations is that the message is not being forwarded to the whole enterprise leading to loss of essential information.

Alpha has encountered similar situations as Delta in the sense of pervasive definition of KPI to facilitate an easier understanding of these indications. Where a message or a visual presentation presents information of events to consider and different people in different professions do not have the same perception of the information. A typical example given by the respondent is where a color indication presented overview that states they did not reach their weekly target per items sold according to their objectives; some people may think that it as a decent effort whiles other people may perceive it to be poor performance. This is because the threshold for when these KPIs should indicate a critical level may be different based on different departments and profession since within the department they may have their own specific goals to achieve. Beta took it a step further by proposing that it is one of the weaknesses working with reporting tools and KPI hence there needs to be enterprise wide discussion for developing a generic KPI which is well understood by the whole enterprise to ensure that the KPI is measuring the desired activity in line with the enterprise goals and "*language*". Else the outcome could lead to suboptimal KPIs which does not achieve its desired goals as it does not transform these facts from the KPI into achievable actions for decision making. Meaning there is a need for not only accurate information in terms of finding solutions but also for enhancing effective decision making in a timely manner:

"*Example, could be that it doesn't matter if Data-Driven Alerts indicates a certain number has been reached [in the dashboard] […] but should instead show valuable or actionable information of what needs to be done [..] to avoid complications [for enterprises] […] Data-Driven Alerts present shallow information [….] that may not be considered sufficient for decision making* " (Beta).

Ease-of-Use

The following concept Ease-of-use from the framework was brought up for discussion regarding the feature. Majority of the respondents that have either interacted with similar features or are aware of its utility describe the essential outcome of the feature as the awareness of an event that have occurred i.e. the *alert* or the *prompt* message, which according to most of the respondents is not difficult to configure in these tools. Epsilon described that regardless of the tools or feature, if the user does not understand its purpose or its utility then adoption of the KPI extension i.e. alerts will not function as was intended to be used as a supplement for awareness to improve one's decision making. The respondent Beta who has implemented BI tools with the associated feature in large commerce enterprises claimed that the settings for these features can easily be configured in modern tools. The respondent elaborated by explaining how it was previously difficult to configure the feature in these tools where it would require several other third-party services for synchronizing and connecting the feature to other services e.g. email, which were difficult to implement and configure. Currently, these modern tools according to the same respondent have these feature in-built without any third-party service involved:

"*However, if you go back several years [….] it was difficult to make Data-driven Alerts work, due to inter-operability problems [with other services and functionalities]. For example, it was difficult to synchronize it with email [….] Nowadays these tools [BI] have this type of functionality built-in to make general alerts within KPI [….] which are also included in self-service tools where you can set up the threshold [for the KPI] by yourself […] previous functionality have been improved and* *simplified […] where a regular user can combine their own dimension [of data] and create reports….* " (Beta).

When it came to the discussion of the use of newly emerged tools and technologies, some of the respondent had different views about it. One of the respondents mentioned that the tools itself have not gained much maturity and effect in enterprises in terms of enhancing performance. Instead, the focus has lied on how to utilize it and make it available at a greater scale within the enterprise than for enhancing decision making:

"*The available tools and its feature is advanced […] however the technology has been developed to a greater capacity for handling big data [processing] […] There's a lack of knowledge on how easy these tools could be for enhancing manager's tasks [in decision making] where at the end it's about trust [in technology and tools]*" (Gamma).

The respondents from the SMEs had a different view as they cited their company size and their market share as a primary factor for the adoption of new technology or further utilizing a particular feature in a greater extent. Where the attention is not focused on how "easy" a technology or its associated feature like Data-Driven Alerts is to employ in their organization. The reason for this explanation according to the same respondents is due to working operationally with these so-called *reporting tools,* meaning interacting with these daily for their given tasks. Therefore, they stated that there are no difficulties in using it either for creating a foundation for decision making or for monitoring internal activities. One of the respondents mentioned that the daily meeting they have within their organization involves among other things discussing critical changes of key values that have occurred in their own dashboards and KPIs. Another respondent from SME explained in a similar manner how the daily meetings they have within their organization centered around information that are considered critical in their KPI where the recorded variations and fluctuations in the values are brought up for further discussions to analyze the extent of impact. During the conversation with Alpha, the respondent mentioned an aspect that may have affected their prioritization of this feature's usability for decision making. This was the difficulty of integrating other services and data sources into the tool which the respondent cautioned and indicated could influence their decision based on what information the Data-Driven Alerts are based on:

"*Other information useful for the tool [to analyze] could be difficult to extract from external systems [….] which doesn't give the effects one wished to have in becoming fully aware of everything [….] you miss opportunities […]* " (Alpha).

The above statement indicates the reliance of making decisions based on one data source. Where the outcome from the decision could lead to suboptimal performance. In terms of the feature, the respondent described that the messages i.e. prompt or the alerts that the tool sends out may not remind them of other operations that have occurred in the periphery of attention due to difficulties of integrating other data sources into the tools that they use. Hence the tools only fetched and processed data from particular data sources, sending messages they may already be aware of.

A technically oriented aspect that Alpha and Epsilon have encountered with KPIs that could affect *alerts* and *prompts* is *"Real-time data".* Something the respondents stated is difficult to achieve due to the delay of collecting, fetching and processing data from various sources to display accurate and current facts in their Dashboard and KPI. However, both respondents also stated the possibility of presenting facts and information which are close to "*real-time*". At the end, we still present past information, this was a common statement by the respondents. When a message is being sent containing information about fluctuations in values in the KPIs, they stressed that opportunities of embracing proactive decisions may not be achievable leading to reactive decisions where the event has already occurred:

"So the tools is more close [to real-time data and information] but not still real-time [….] The indications [of the alerts and message] allows for a general understanding of the past […] through breaking down the KPI [Drill-down] into smaller pieces […] enables a better and in-depth understanding of what happened during certain key-activities [of business performance and processed] " (Alpha).

"*We have dashboards that displays key values for functionality for ****** warehouse [.....] the software must be responsive [real time] for ******, to show how long it takes to execute certain functions […] if it's not responsive then the message queue for the alerts will be to high [……] where we are not able to provide first hand support before it's too late […]* " (Epsilon).

In accordance with Alpha, another respondent mentioned that analytics can provide the *"real time"* information with more accuracy compared to reporting and monitoring with KPIs and dashboards. These advanced algorithms can predict future events and facilitate interaction with meaningful information for decision making. Furthermore, the usability of interaction with advanced BI tools according to the same respondent provides an opportunity to incorporate a threshold in an enterprise's KPI and dashboard. The respondent explains that based on the data, these tools can predict when in time a certain threshold will be reached. According to the same respondent, to achieve this type of scenario with a greater extent of use of this feature in advanced tools would require several amounts of data sources as well as the organization's IT-infrastructure being considerably advanced with the ability for prediction and forecasting. The respondents meant therefore that implementing and understanding the value of applying new advanced analytics may be difficult to understand due to its advanced algorithm and parameters. This the respondent believes could be difficult to interpret compared to KPIs which can be easily understood by enterprises who already have the experience from working with KPIs and Dashboards for their tasks.

The respondents Alpha, Beta and Epsilon offered opinions that for the features to be effective in use for decision making, data quality is an important factor to be considered when evaluating the accuracy of fluctuating values that these alerts produce for decision makers to consider thus whether the threshold for a counted value has been truly reached or not. Otherwise, the respondents expressed that this could lead to low trust in its usability hence more effort should be placed on ensuring the accuracy of the feature to further improve its utilization. Beta expressed the need for some form of structure or mechanism in place which could manage and serve as quality assurance to vet and prevent facts that are false or unrequested from being displayed on these dashboards and KPIs.

"[…] the quality of data is important […] for KPIs to present accurate information about values that are also correct [in its indication of the value]. If not, it would show false indications that leads to you [decision maker] taking wrong decisions […] you [the decision maker or the BI user] have to drill-down to see its original form [the source] to see if the indication [the message of the alert or the prompt] is correct or not " (Alpha).

"*Data Quality is an important issue that needs to be discussed and solved [….] when there isn't a structure for data collection […] of what is being collected and how it's being measured [….] to know what is being measured to prevent suboptimal KPI*" (Beta).
"*Getting the right data in the right format […] there is a lot of thinking on how the data can be transformed into the right format [….] Because if you have bad data, then the alert will indicate wrong statuses […] people will stop paying attention to the alert [….] Great effort goes into getting the right data in the right format and setting alerts to appropriate level of the correct data*" (Epsilon).

Actual Use

During the last phase of the interview with the participants, discussions about the further utilization of Data-Driven Alerts features to a greater extent for decision making were brought up around the framework concept of actual use. The discussion was mainly concentrated on future successors of the feature replacing its usability with better performance in predicting the future and therefore improving an enterprise's decision-making process in respective industries. One of the respondents explained that in the near future enterprises in general will start using analytics and the capability of making automatic decisions extensively where Reporting tools or Decision Support Systems as we call it with features of sending alerts will be used more often for enterprise operations and business processes. Meaning that automated decision making will be on the increase with some form of human supervision included where alerts will be included in these advanced tools and technologies as a form of indication to business executives that a decision should be taken regarding an activity within their enterprise.

Gamma who has researched extensively in the automotive and manufacturing enterprises asserted that due to the increasing data that enterprises collect and store, it is essential to employ advanced analytics e.g. *predictive* and *prescriptive* on a greater scale in order to gain competitive advantage in finding meaningful insights that enables one to be more innovative. This can be difficult to achieve even if the reporting tools i.e. BI tools have advanced features and capabilities of sending messages on events that have occurred:

"To gain competitive knowledge [….] there is a need to start adopting analytics for their use and institutions [organizational structure] to know that there's a greater value to receive compared to traditional approach [reporting and KPI alerts] [….] not to incorporate this into decision making will lead them [enterprise] to lagging behind in competition […] However, analytical tasks and automation should be implemented incrementally to complement the human capacity in these enterprise [for decision making] " (Gamma).

From the SME perspective, Delta describes the opportunities of considering advanced analytics and technologies to enhance their decision-making processes compared to the present tools used for decision making. At the same time, the respondent also stated that their current tools have been optimal in executing current tasks for their decisions and operations. Regarding adopting new advanced tools with predictive analytical capabilities, Delta explains that this would require effort from the managerial and organizational perspective:
"*if we are considering to implement these tools [of predictive capabilities] because of our customers' unexpected demand of different products that we were not aware […] then this would require a lot of planning and resources to implement [……]* " (Delta).

6. Analysis

In this section, we will further analyze the previous section extensively and in depth to obtain a better understanding of Decision support and Data-Driven Alerts usability in the context of decision making. This will be achieved by briefly reviewing and reflecting the topics that the respondents discussed to interpret the meaning behind them by applying TAM qualitatively as a thematic lens where the essential codes from the thematic coding is presented in cursive form. Then organized and processed around the different key concepts from TAM and the added category i.e. *Definition and Perception of Data-Driven Alerts* to indicate potential patterns from the processed material from the conducted semi-structured interviews. Furthermore, we will briefly analyze the feature's usability by applying the SWOT model which was explained in previously where our aim will be to ascertain how Data-Driven Alerts affects decision making.

Definitions and Perception of Data-Driven Alerts

As we can see from the interviews there are no universal definitions for the feature and thereby the respondents describe the purpose and usefulness in different ways. The common thread that runs through the description of Data-Driven Alerts is that it is a feature that allows the capability of getting *predefined notifications* on requested fluctuations that occur in dashboards and KPIs with the aim of minimizing the time and the effort required for monitoring and controlling business performance. In the sense of efficiency, it liberates personnel from constantly monitoring a dashboard and its associated KPIs.

The respondent does no however perceive that the feature is being used for its original purpose, which is getting notifications or alerts when they are away from their dashboards. The reason could be that it is not fulfilling the respondent's perception of becoming *proactive* and *aware* of events before they occur. Hence it is not considered effective for decision making to increase their business performance. This could be identified from the representative of the large enterprise where their major concern is to detect an *upcoming event* and act on it by making decisions that could be profitable for them.

Perceived Usefulness

The respondents that works in SME, seemed to have either *low* or *no needs* for of Data-Driven Alerts based on its *designed use case*. The reason for this as could be seen from the previous section is in their constant interaction with their own tools in relation to reporting and monitoring. Therefore, there is no need for utilizing the feature in a *greater extent* than only using color indications to remind the user behind the dashboard to further analyze an occurrence in these KPIs by drilling down. Where one of the respondents described the *inadequacy of reporting* tools due to the *insufficient information* given which may not satisfy their needs for a deeper and broader understanding of past events which is in accordance with Davis (1993) explanation of user acceptance regarding features that satisfies a user need. Hence further explanation needs to be obtained through analysis to a more detailed level by giving the interpretation of the causes of an event. This the representatives from the larger enterprises indicated gives *low* or *no business value* for their enterprises in achieving *competitiveness*. Their perception of how useful the feature is for decision making does not fulfill their desired goal which Bach et al. (2016) emphasizes needs to be considered in order to become more proactive and therefore does not seem to be a *lucrative investment* for large enterprises hence the preference for *advanced analytics* i.e. predictive analytics. However, one of the respondents from the larger enterprise responsible for monitoring activities gave some applicable instances where Data-Driven Alerts could be used for *automatically monitoring* critical fluctuations much more efficiently and remind those in charge to act on issues before they escalate.

The perception of *business value* which the respondents from the large enterprises indicated is information that satisfies their needs to enable business executives to make strategic and tactical decisions by providing them with *future insights* about their markets, customers and competitors. This enables large enterprises in respective industries to make *proactive choices* and put them in the lead with competitors. However some of the respondents mainly SME and Epsilon stated that the alert feature depicted as a color indication enables an enterprise to *liberate personnel* and time from manually monitoring several operations and activities that occurred within the enterprise therefore fulfilling the usability of the feature of being efficient which is in accordance with Davis (1993) explanation and is considered to be one of the motivational factors for adopting this system design feature. For professionals like a business controller responsible for overseeing and reporting anomalies to top management, there is proof to some level that the Data-Driven Alerts feature improves performance or facilitates their work. For operational decision making, this feature could be considered useful in the sense that it aids in being proactive in *detecting anomalies* within their operational processes which may otherwise interfere with other linked business activities. Therefore, this type of feature may not be considered appropriate for strategic and tactical decision-making in large enterprises in general although it could be very helpful in monitoring scenarios. However, the respondents also indicated that additional effort is required to assert the accuracy and precision of the alerts to ensure dependability and trust as a quality assurance measure.

Ease-of-Use

According to the respondents' answer, the feature itself can easily be configured in different tools that are being used currently as compared to how it was previously. However, there are some issues that affects interactions with the tool's features and performance for decision making such as *data quality* and *infrastructure* where data is being fetched and processed into presenting requested fluctuations in values that occurs in dashboards and KPIs. This affects the usability of the feature's characteristics as it becomes less prioritized due to these issues. To emphasize the effects of these issues, the respondents explained that it affects the user perception of *how much effort is required* to interact with the feature in order to receive the best results which corresponds to Davis (1993) explanation of the influence it has on the perceived usefulness and attitude of the user against the feature. This could clearly be seen when several of the respondents discussed that if the data does not contain the *accurate values or measures* corresponding to the right activities then the alerts that are being produced by this feature will be as they put it "pointless". Even though the tool itself is user-friendly and easily understood by its users, it still requires considerable amount of effort from an organizational perspective of managing the complex issues regarding data quality. Something that will also characterize the use of emerging technologies in advanced data analytics where this issue will be more evidently critical since the aim is to predict and forecast future events to enhance decision making.

The ease-of-use of the features is no longer the major factor being considered when it comes to the *incorporation* these features into decision making processes, where Lah et al. (2020) indicates that influence is the extent to which the use case of a feature and its tools has. Rather the attention is on the technical aspects that characterizes the use of this feature or new technologies, which Davis (1993) means either complicates or facilitates the use case in conjunction to other systems. The tools have been developed in a positive way in terms of its user friendliness whereby its functionality and features are well understood by its users. The focus of the feature is on the value which is the *information that the alerts provides* and its use case for decision making as indicated in several of the respondent's tasks and business activities. Where one the respondent in the previous section described that the focus of similar features or new technology is on how to integrate it into an enterprise or organizational structure to improve decision making.

Actual Use

What we can see from the interview is that in order to gain more business value from adapting Data-Driven Alerts feature, it would require a *synergy* between emerging new technologies e.g. predictive analytics and incorporating alerts/ prompts at a greater scale to coincide with Bach et al (2016) explanation on the acceptance of a features into the user's use cases and tasks. Whereas it seems from the respondent's answer that they perceive this functionality or feature not to be useful compared to other emerging technologies due to the effort required for further investigation to understand why an event occurred due to the shallow information provided by the alerts, enterprises nevertheless are moving towards adopting new technologies and analytics for better decision making to achieve their desired goal of becoming more *proactive*, *competitive* and *innovative*. This therefore affects Data Driven Alerts feature's attractiveness for enterprises especially for larger enterprises in terms of *adopting* and *incorporating* it at a greater scale for use in decision making. This also corresponds with Davis (1993) explanation of adopting a certain tool or technology which relates to the return on investment being a critical factor which can only be achieved when ones needs are fulfilled.

SWOT

The strength of the feature in a decision-making context is derived from the analysis of the respondents in this previous section. It facilitates an enterprise's ability to monitor its activities and business performance through pre-defined conditions. The tools will automatically alert when any of the levels in their requested KPI have reached its threshold, liberating personnel from manually monitoring to instead taking decisions for mitigating or enhancing a situation. The information that these alerts contains i.e. messages gives an overview of what has happened or "is happening" in their organizations which in some sense enables quicker reactions compared to manual monitoring. The tools that have these features built-in are easy to configure hence is user-friendly according to the respondents. Data-Driven Alerts are therefore an appropriate choice to adopt in an enterprise that have many operational activities that needs to be monitored for efficiency purposes.

However, the weakness that the respondents points out is among other things the message that the alert sends which contains information about events that have already occurred leading to reactive decisions making. Due to the difficulties of achieving "real time data", these alerts will only notify a user or a decision maker with a descriptive event which according to the majority of the respondents does not meet the needs of their respective enterprises. Furthermore, the alerts give insufficient information to be data-driven and serve as a foundation for decision making. It does not explain the reasons for the occurrence of an event hence the respondents stated that extra effort is required to perform drill downs for details concerning alerts from respective KPIs in order to deduce the root cause. Therefore, enterprises become vulnerable and inefficient in reorganizing their human resources after an event occurs even though their goal is to be more prepared and aware hence making it difficult to achieve a proactive decision-making culture.

The future for the Data-Driven Alerts as it stands now according to the respondents does not seem appealing due to preferences of advanced analytics which performs better in producing valuable information. This is because enterprises could gain knowledge in taking proactive decisions enabling them to be more competitive by being more data driven. The existence of the feature is therefore threatened by advanced and emerging technologies in the field of analytics that outperforms reporting tools in decision making.
The figure 6 below, presents a summary of the SWOT model, used for analyzing the Data-Driven Alert usability use case for decision making.

To increase its usage by developing this feature to be more appealing and attractive to enterprises in order to enhance its adoption at a larger scale for decision making, it will need to be incorporated and integrated with advanced analytics in a symbiosis to execute the use case of alerting that an event may occur based on predictive analytics. This will inevitably make it more relevant leading to a higher adoption rate and increase the user's opportunity to make accurate, efficient and effective decisions.

Strength Facilitates monotoring Overview Easy Settings Operational decision	**Weakness** Descriptive information Shallow Information Reactive decision Tactical and Strategic decisions
Opportunities Incorporating with advanced analytics	**Threaths** Emerging analytics technologies

Figure 6: SWOT over Data-Driven Alerts' usability and its use case

7. Discussion

This chapter follows a discussion on the analysis of the study in connection to the literature review to enhance the significance of the research results and findings from different perspectives. Therefore, the chapter will follow the coherent structure of the framework's subchapter where relevant literature from the *Literature review* section will be brought for discussion in accordance to the analysis of the empirical material. The concluding sections of the chapter will elaborate on the contribution to the identified gap in academic research on the subject area.

The purpose of the research was to conduct an empirical study on how Swedish companies and enterprises located in different industries apply BI tools with Data-driven Alerts features for decision making whereby we further studied the characteristics of Data-driven Alerts in terms of usability from the perspectives of different industry professionals through TAM. The research questions that initiated the study were as follows:

- How is BI related to decision-support systems and Data-driven Alerts currently applied at Swedish companies in different industries.
- How do practitioners perceive data-driven alerts as tool to enhance their decision-making processes?
- How do leaders and managers perceive the usefulness and ease-of-use of BI related to decision-support systems and data-driven Alerts?

Based on previously presented literature in the *Literature review* chapter, we will further investigate the above purpose and its questions to broaden understanding of the subject to increase further knowledge.

Definition and perception of Data-Driven Alerts

As it can be seen from the analysis, companies in different industries are still using reporting tools for monitoring and overseeing internal activities which has an impact on the company's performance especially with case from the SME perspective. As mentioned by the respondents, KPIs and Dashboards enables companies in general to increase their awareness of business performance for efficiency purposes whereas Data-Driven Alert provides them with a platform to leverage its capabilities for alerting anomalies in business processes to enhance efficient human resource management. Chen et al. (2012) would classify the company's use case of their tools and data-driven alerts as *descriptive analytics* due to the use case of monitoring and reporting key values that indicates a company's business performance. Ibrahim et al (2017) explains that these tools being used in dashboards and KPIs have been improved to present information in close to real-time scenarios. Some of the respondents however indicated that it is somewhat difficult to achieve because systems have delays in fetching and processing data from source systems into their KPIs and Dashboards.

From what we gathered, the feature has the ability and potential to be perceived as a complement for efficient operational use cases and decision-making scenarios. Meaning that even though there is a delay in the alerts, they could be used for reporting anomalies that occur within BI products which is very helpful in an operational context and in so doing redirect expertise to tackle much more pertinent and critical organizational challenges. If this is done then according to Boyton et al (2015) the organization will be able to achieve ROI from implementing the BI solution. This was also expressed by one of the respondents who alluded to the fact that it liberates human resources from manual operational tasks regarding monitoring these KPIs and Dashboards. In accordance with Bucher et al (2009), it is explained that the purpose of KPIs and Dashboards is mostly effective in operational use cases and decisions making for reasons of achieving the right trajectory in relation to company goals and objectives in order to create awareness and control for improving incident management.

Perceived usefulness

As discussed, Data-driven Alerts and other BI products have a positive impact on operational decision-making and processes. In the analysis, it could be seen that most respondents have low needs for adopting Data-Driven Alerts for decision making based on its designed purpose which is receiving alerts remotely when they are away from their posts that an event has occurred that requires their immediate attention i.e. decision making. We considered the design of the intended use of the feature to be a matter of integrity. Where personnel and professionals such as leaders and managers do not want to be interfered with work related tasks during spare times. This could be seen from the nature of responses given by most of the respondents who indicated that alert fluctuations are useful when they were at work behind their dashboards. Furthermore, the respondents indicated situations where flaws occur in indications and related this to be possible with Data-Driven Alerts. In a similar manner to what Fletcher et al (2017) describes as *fatigue alerts* to medical practitioners where systems sends responses or alerts that are not accurate i.e. false alarm which led to the practitioners loosing trust in utilizing the feature. We believe that this could be one of the reasons why respondents considered the usefulness of the feature based on its designed use case as low.

Another reason for the low perceived usefulness of alerting features from the respondent's perspective is the need to become more proactive which is presented several times in the empirical result. This is because reporting tools and its features present information on past events that have already occurred due to lack in achieving *real-time* or up-to-date information on demand. This according Tunowski (2015) decreases the business value in regard to latency in taking decision based on information that is processed and available when requested, where the sooner the event that occurred is presented, the more value gained if decisions are taken to combat the event i.e. *the actions* to mitigate or embrace the consequences of an event (see chapter *Business Intelligence as a process – figure 3*). Ibrahim et al (2017) found in their study that technical resources in bandwidth are required in order to make present and current information available. The factor for this consideration is similar to what the respondents emphasized during the interviews which was that dashboards and KPIs present an overview of their progress and performance which is insufficient to base future actions such as tactical and strategic decisions on. Where the alerts for decisions is not considered applicable for managers and leaders in their respective investigated companies. The reason for these considerations from managers and leaders in tactical and strategic positions can be based on the Schmidt and Willhelm (2000) explanation of a company's success being based on choosing the right path for their future i.e. trajectory. If the feature and its tools allow for further understanding of occurrence of an event then according to Baars et al (2014), this would enable managers to explore and become familiar with the data through Self-service which will empower them to make decisions where experience from the past is combined with visualizing an event through statistical measures. We see this as becoming more data-driven with more reporting and operational tools now offering capabilities for self-service explorations and visualization for decision makers and hence alerts could be useful as preventive measures based on past experiences available in the data. In accordance to the Boyton et al (2015) explanation of allowing possibilities for users to analyze the data in their own preferences for decisions, this according to our analysis of empirical data may provide managers and leaders with sufficient information needed to empower strategic and tactical decision-making.

From our analysis, we found that most of the respondent preferred advanced analytics i.e. predictive analytics for tactical and strategic decisions which according to them enables useful insights about their customers and competitors enabling them to be more competitive in their respective business environments. This therefore receives more value in decision making compared to reporting tools with data-driven alerts features based on the organizations quest to become proactive before an event occurs. This is coherent with what the literature discusses as the benefits with predictive analytics.

Lepenioti et al (2020) explains that more value is obtained through applying Machine Learning and AI due to information that describes *What* and *Why* an event will occur and happen, which mangers and leaders need for decision making according to our analysis. Also, Lepenioti et al (2020) described an exceptional use case of becoming proactive, giving an in-depth and detailed analysis of information about a company's customers and competitors (Jaklič et al. 2018). This we also believe enables to shorten the time span required for decision making (Tunowski 2015) and brings more dynamic capabilities which Teece et al (1997) considers to be important in a competitive environment. Based on the above assertions, we draw the conclusion that advanced analytics is more powerful for strategic and tactical decisions where data-driven alerts do not enable proactive capabilities in predications base on how the use case for the feature is currently being applied and adapted.

Ease-of-use

When it comes to the issue of configuring and integrating Data-Driven Alerts in respective tools according to the respondent, it is not complicated compared to how it was previously. From the analysis, the factor that affects and complicates the feature's use case is the difficulties of managing data quality where if this is not adequately managed the reporting tools and Data-driven alerts will present inaccurate information. This is something Watson (2009) determines to be important because it affects the decisions itself due to basing the decision on false or inaccurate information. We believe that for companies to become more data-driven by adopting new advanced analytics, this problem needs to be resolved by prioritizing data quality assurance measures since this is a critical issue in the organization as indicated by one the respondents. By having mechanisms in form of policies that relate to responsibilities and task areas for how data should be managed safely and accurately to facilitate the use case of Data-Driven Alerts and advanced analytics in general. This is in accordance with Watson (2009) where this policies needs to be incorporated into the company's strategy. However, we still believe that this agenda should be pervasive and not to be considered as an IT-issue as more and more processes and tasks are becoming digitalized (Olszak 2014). Therefore, we believe that once this issue has been resolved, it may be easier to evaluate the respondent's perception in regards to the concepts of ease-of-use due to the IT-infrastructure that these tools and features are being operated in.

Actual use

Our analysis shows that it will be difficult to gain more value in adopting Data-Driven Alerts to a greater extent based on its designed purpose and current use case due to our respondents firmly indicating their preference for adopting advanced analytics for tactical and strategic decision making to increase a company's business value. As previously explained, Lepenioti et al (2020) states that at the end of the decision making process in relation to advanced analytics, decisions will inevitably return to a descriptive basis as a means to confirm and follow-up on the selected choices from a human agent in order to ensure efficiency and to learn lessons from the performed actions (see figure 4 in chapter *Literature review – Descriptive, predictive and prescriptive analytics*). We see this as an opportunity for reporting tools and Data-Driven Alerts to be in symbiosis with Advanced Analytics in decision making contexts to improve its outcome, quality and user friendliness. We believe that all of the analytics previously presented supports each steps in Shollo and Kautz (2010) explanation of *BI as a process* where each analytics has its own purpose in decision making and therefore we believe that this could be one of the reasons why we have different value creation in decision making. This can be seen in previous sections of the analysis where the usability of Data-Driven Alerts served various functions and purposes for the different kinds of decisions that occur in an organization (see chapter *Analysis: SWOT* - figure 6).

Contribution to The Gap Between Practice and Academia

As we previously explained regarding the lack of research about Data-Driven Alerts and its designed features for decision making, we have considered to fulfil this research purpose by contributing new knowledge about the research subject. Especially, how Swedish companies in different industries apply and work with BI and its associated systems where the focus has been on the uninvestigated BI feature called Data-driven Alerts. We have investigated leaders, managers and other relevant professionals about their perceptions of BI and its features by applying TAM as our theoretical framework i.e. thematic lens in a qualitative manner, where we found out that the feature's designed use case for decision making and proactiveness has not been adopted to a great extent due to it being considered as not optimal for adoption in strategic and tactical decision-making instances. Furthermore, in this study we have contributed further knowledge in the research domain of BI and its associated concepts of technologies, process etc. by shedding light on the trajectory of BI. We have managed to propose based on empirical evidence what the expectations and perceptions are from professionals and academia in terms of what BI in the future should consist of in a decision-making context. Thereby, we have fulfilled the gap of BI in association with decision support systems, Data-driven alerts, and its perception of usability in decision making in the field of Informatics.

Suggestions for Further Studies

In this study, there is a lack of discussion about implications and challenges of data-driven technologies for decision making and advanced analytics. As we can see from our study, it is clear that BI is moving towards advanced analytics which our study indicates enhances decision making at a strategic and tactical level in a competitive organization. Therefore, it would be interesting if further research with other research methodologies such as observations could be undertaken to study challenges and implications that occur when advanced analytics is being adopted in a larger scale for enhanced decision making in the similar companies that we investigated as means of conducting a character type of a normative study to provide guidelines based on the findings unraveled in this study. As previously mentioned, decision making is a human activity where the decision maker has limited cognitive abilities in processing information and taking decisions based on the available information hence is bounded by human rationality (Simon 1959). This indicates that in the near future companies need to consider this as an important issue to be managed in order to enable a smooth transition in integrating advanced analytics into their organization and incorporating it with other business activities (Boyton et al. 2015) since decision making is an activity that occurs in different business processes and at different levels within an organization.

8. Conclusion

To understand what we have endeavored to unravel in this study, the research question will be presented followed by its own formulated answer.

- How is BI related to decision-support systems and Data-driven Alerts currently applied at Swedish companies in different industries.

BI has moved to advanced analytics where the respondents considered this to be related to the BI domain since its major capability is to enable its users to make powerful decisions by being more proactive by leveraging advanced computational algorithms to produce enhanced insights from information in order for them to gain a competitive edge irrespective of their business environment. The Data-Driven Alert feature is considered to belong to descriptive analytics and reporting tools, where BI products such as KPIs and Dashboards are the focus. However, after careful consideration and dissection of the empirical results from the respondents perception and views along with other literature we have discovered that there is a possibility for this type of feature and use case of Decision Support systems and Data Driven Alerts to become extremely relevant by virtue of their functionality being embedded into emerging advanced data analytics and technologies. This is due to the functionalities it provides for companies in terms of efficiency and effectiveness where companies still want to achieve control over their activities whereby reporting tools are most convenient and useful for that purpose.

- How do practitioners perceive data-driven alerts as tool to enhance their decision-making processes?

As previously shown, the traditional use case of BI in terms of reporting, Decision support systems and newly developed features of Data-Driven Alerts are most beneficial and impactful if adapted for operational use in internal activities due to its dynamic capabilities and analytics features being more appropriate for monitoring processes but will however need to be enhanced to facilitate proactive decision making if it's to be considered for adoption in tactical and strategic decisions-making scenarios. Therefore, practitioners interviewed in this research perceive data-driven alert as tool that is capable of enhancing their operational decision-making processes.

- How do leaders and managers perceive the usefulness and ease-of-use of BI relating to decision-support systems and data-driven Alert?

The respondents' perception of Data-driven Alerts is based on their experience with tools for decision support systems which have integrated this feature into their designed use case which does not seem to have high business value to the respondents compared to advanced analytics. This is due to the fact that the investigated companies have not utilized the feature according to its designed use case of BI tools and decision support systems. Therefore, it is considered not be attractive or powerful enough to adopt for complex decision-making instances which requires thorough, accurate and in-depth information on what to implement further actions on. Therefore, we determined that these are not desirable for leaders and managers in companies to consider for adopting on a larger scale in terms of its current use case and utilization. However, these tools and features does seem to have tremendous business value in the operational divisions of organizations for decision-making. This is because these alerts make them aware of events relating to systems or clients that require attention to prevent further exasperation leading to loss of revenue, where most often than not there is enough time to apply damage control measures to curtail further adverse consequences. As a result, we consider the feature to be effective for use where other factors of technicality do not impede its use case.

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10. Appendix – Interview Guide

1. **Before initiating the interview:**
    - Introduce ourselves
    - Introduce the purpose of the study and the research subject
    - Ask if we can record the interview for transcribing and tell them about the confidentiality about their information.

2. **Basic information about the respondent:**
    - Ask them about their organization
    - Ask them about their profession and tasks
    - Their organizational department & unit
    - Experience in years

3. **Topics for the main interview:**
    - What is your perception of *Data-Driven Alerts?*
      → Strength and weakness.
      → Opportunity and threats that either promotes or complicates its use and usability in the near future?
      → encounter?
      → How do you currently track/monitor changes that are important to you?

    Ease-of-use:
    - Main difficulties that arises in Analytics/BI in terms of interaction?
      → Challenges in *decision-making*?
      → Difficulties and challenges in BI-community and BI-tools?
    - Estimation of effortlessness that *Data-Driven Alert* have promoted in work-related assignments and decision-making?
      → Why?
      → How so (an example)?
      → Monitoring (Dashboard & KPI)
    - Difficulty with current Dashboards, in terms of monitoring and developing?

    Perceived usefulness:
    - How does Data-driven Alerts facilitate or prevent you from performing your work tasks?
      → In *decision-making*?
      → Creating reports
      → Creating Dashboards, Monitoring KPI
      → Informing the decisions and reports?
      → Why?
      → How so (an example)?
    - How could it harm or improve one's decision-making?
      → Why?
    - What is lacking today in BI-tools for decision-making?
      → How could that be improved?

    Actual System use:
    - How would you perceive the future of utilizing the feature, in terms of the extent of adopting *Data-driven Alerts* in a broad scale?
      → Why?
      → How so?
      → Automated decision instead of Data-Driven Alerts?

4. **Round off the interview:**

- Ask the respondent if they wish to elaborate more on previous questions.
- Ask if there were questions that we forgot to ask, that they would like to express.
- Round off the interview and declare that the interview is over!

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