# BIG DATA VALUE CREATION AND CAPTURE WITH AN IOT SOLUTION

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JYVÄSKYLÄN YLIOPISTO

## ABSTRACT


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*Abstract*

Organizations have taken an interest in big data and how they can monetize it. When monetizing big data, it can create a new way to do business and to accomplish it successfully, companies need a business model to do so. Value creation is important when capturing value and considering a business model, so it is beneficial to understand better where the value stands in big data, specifically data that is gathered form an IoT device. Data's value and value creation has been studied before but the new context of IoT gathered data can provide new insights of the characteristics of valuable big data and add to the value conversation. It is also interesting to find out how IoT changes the value creation process of big data.

There is a need to study big data monetization in the context of IoT. IoT and its business model studies are still relatively new, so more research is needed. This research answers that need by studying big data and IoT with a research question *'What kinds of business models do companies use for value capture with big data solutions when the data is collected from IoT devices*?'.

Data often needs some kind of processing or analysing to give insights and to create value. With value creation and capturing the value itself is an important aspect and this study also tries to find answers to questions: '*What kind of big data is considered to be valuable for the customer*?' and '*How is big data value created and how does IoT change the value creation and capture big data?*'. The research is in the context of b-to-b companies that operate in Finland, and the research questions are studied though the seller's point of view.

The theoretical background consists of value creation and capture theory. First an understanding of big data and IoT are made after which their value and its creation are examined. Then value capture is studied focusing on the business model theory of big data monetization and IoT.

In addition to literature review, a qualitative research is conducted to answer the research questions. The research consists of six semi-structured thematic interviews of b-to-b companies that offer a big data product where the data is gathered by the means of IoT, and the resulting research data is analysed with a thematic analysing method.

The results of this study reveal that information that can be used to predict the future or model the world around us is considered valuable. IoT provides real time data which can help to prevent value loss in data collection and processing latency. IoT itself is largely seen as a means of collecting data but it also helps by simplifying and making the value creation of the data and its processing easier.

The companies see that their big data offering is more valuable than just the value of the data, it is seen as a solution to their customers' problems. With the offer, they both create add value for their customers and support the sales of their company's main products. To capture this value a SaaS-business model (software as a service) is often used, in which the customer does not have to buy the necessary software theirself, but the supplier provides it as a service. Another interesting finding is that in larger companies where big data is not the company's main source of revenue, IoT is used to provide new digital functions and services to the existing product. On the other hand, smaller companies where service is their main source of revenue focus on selling sensor data or digital services where IoT components are part of the service price. Most of the companies thought their offers to be unique, or at least in their own industry. However, they don't believe that their business model is unique.



*Keywords*
Big data, IoT, Internet of things, value creation, value capture, business model

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*Tiivistelmä - Abstract*

Organisaatiot ovat kiinnostuneet big datasta ja siitä, miten ne voivat ansaita sillä rahaa. Sitä varten organisaatio tarvitsee liiketoimintamallin. Liiketoimintamallia luotaessa on tärkeää ymmärtää mikä IoT:sta kerätyssä big datassa on arvokasta ja miten sitä pitäisi analysoida ja jatkojalostaa, sekä miten luotu arvo saadaan myytyä. Tiedon arvoa ja sen luontia on tutkittu aiemminkin, mutta IoT:lla kerätyn tiedon tuoma uusi näkökulma voi tarjota uusia oivalluksia big data -ominaisuuksista. On myös mielenkiintoista selvittää, miten IoT muuttaa big datan arvonluontiprosessia.

Big datan kaupallistamista on hyvä tutkia lisää IoT-kontekstissa, sillä IoT ja sen liiketoimintamallitutkimukset ovat vielä suhteellisen uusia. Tämä opinnäytetyö vastaa tähän tarpeeseen tutkimalla big dataa ja IoT:ta tutkimuskysymyksellä: *millaisia liiketoimintamalleja yritykset käyttävät arvon haltuunottamiseksi big data -ratkaisuilla, kun tietoja kerätään IoT-laitteiden avulla?*

Big data tarvitsee usein jonkinlaista käsittelyä tai analysointia luodakseen oivalluksia ja arvoa. Arvon luomisessa ja haltuunotossa on tärkeää ymmärtää mikä sen arvo on asiakkaalle. Tässä tutkimuksessa yritetään täten löytää myös vastauksia kysymyksiin: *Minkälaista big dataa pidetään arvokkaana asiakkaalle?* ja *Kuinka big data -arvo luodaan ja miten IoT muuttaa arvon luomista ja haltuunottoa?*

Teoriaosuus koostuu arvonluonti- ja haltuunottoteoriasta. Ensin käsitellään big dataa ja IoT:ta, minkä jälkeen tutkitaan niiden arvoa ja arvonluontia. Lisäksi arvon haltuunottoa tutkitaan keskittyen big datan kaupallistamisen ja IoT:n liiketoimintamalliteoriaan.

Kirjallisuuskatsauksen lisäksi laadullisessa tutkimusosuudessa tutkimuskysymyksiin haetaan vastausta tekemällä kuusi puolistrukturoitua teemahaastattelua. Haastateltavana on Suomessa toimivia b-to-b yrityksiä, jotka tarjoavat big data -tuotetta, jossa tiedot kerätään IoT:n avulla. Tuloksia analysoidaan temaattisella analyysimenetelmällä.

Tämän tutkimuksen tulokset paljastavat, että tieto, jolla voidaan ennustaa tulevaisuutta tai mallintaa ympäröivää maailmaa, pidetään arvokkaana. IoT antaa reaaliaikaista tietoa, joka auttaa estämään arvon menetystä tiedonkeruun ja analysoinnin käsittelyviiveissä. Itse IoT nähdään suurelta osin keinona kerätä tietoja, mutta se myös edesauttaa yksinkertaistamaan ja helpottamaan tietojen arvonluontia ja käsittelyä.

Yritykset näkevät, että heidän big data -tarjontansa on paljon muutakin kuin pelkän datan tarjontaa, se on asiakkaiden ongelmien ratkaisua. Tarjonnalla he sekä luovat asiakkailleen lisäarvoa että tukevat oman yrityksen päätuotteiden myyntiä. Palvelun toteutuksessa käytetään usein Saas-liiketoimintamallia (Software as a Service), jossa asiakkaan ei tarvitse hankkia tarvittavia ohjelmistoja itse, vaan toimittaja tarjoaa ne palveluna. Mielenkiintoinen löytö on myös se, että suuremmissa yrityksissä, joissa big data ei ole yrityksen tärkein tulonlähde, IoT:tä käytetään tuottamaan uusia digitaalisia toimintoja ja palveluita olemassa oleviin tuotteisiin. Toisaalta pienemmissä yrityksissä, joissa palvelu on heidän tärkein tulonlähteensä, keskitytään sensoridatan myyntiin tai digitaalisiin palveluihin, joissa IoT komponentit ovat osa palvelun hintaa. Suurin osa haastatelluista yrityksistä piti tarjouksiaan ainutlaatuisina vähintään omalla alallaan. He eivät kuitenkaan usko, että heidän liiketoimintamallinsa olisi ainutlaatuinen.

*Asiasanat*
Big data, IoT, Internet of things, arvo, arvonluonti, arvon haltuunotto, liiketoimintamalli, esineiden internet, tiedon analysointi

*Säilytyspaikka* Jyväskylän yliopiston kirjasto

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# 1 INTRODUCTION

## 1.1 Study background

Big Data has been a trend for over a decade now, but the interest in it is still strong (Google Trends, 2020). According to New Vantage Executive survey (2018) ”*97,2% of organizations are investing in big data and AI*“ (Petrov, 2019). Being able to analyse and use big data to one’s advantage promises enhanced service for the customer, and profitability to the company (Farah, 2017). This active asset is also a new novel source of revenue that can give competitive capability to its owners when used right (Hanafizadeh & Harati Nik, 2020).

The amount of data is in a fast, constant influx. Petrov (2019) demonstrated an IDC study’s prediction to be roughly right: between 2010 and 2020 the amount of data in the world has doubled every two years. In 2018, the daily amount of data created was 2,5 exabytes (DOMO, 2018) and it is estimated that the number will be 463 exabytes by 2025 (Desjardins, 2019). That is about 185 times bigger in 7 years!

One reason for it is the internet of things (IoT) which is a way of gathering big data fast. It’s a combination of a physical product (“thing”) and a digital aspect (“internet”) and the amount of them is growing quickly. According to Statista, there will be 75 billion IoT devises in 2025, while the number was 26 billion in 2019 (Jay, 2019).

Organizations have recognized IoT as a new up and coming trend that is a game changer in multiple industries and it is thought to disrupt existing business models (Wortmann, Herhausen, Bilgeri, Weinberger & Fleisch, 2020). Also, according to a Microsoft survey (2019) 85% of big organizations are taking on IoT solutions globally and the percentage is thought to reach 94% in 2021.

Big data can be seen as a tradeable resource (Niyato, Alsheikh, Wang, Kim & Han, 2016a) and companies want to use their big data to create revenue (Woerner & Wixom, 2015). Data monetization is a term used to describe this process of generating profit from data (Faroukhi, Alaoui, Gahi & Amine, 2020; Hanafizadeh & Harati Nik, 2020). Najjar and Kettinger (2013) defined it as converting data’s intangible value into real value or into other tangible benefits. Wixom (2014) defined it as ”*the act of exchanging information-based products and services for legal tender or something of perceived equivalent value*”.

There is an interest for big data monetization also in the business world. A research from EY and Nimbus Ninety (2015) reveals that: 35% of the study participants said a top driver for implementing data analytics was to monetize existing data, and about a third are using big data services and products to complement their business model. Gartner (2015) predicted that 30% of businesses monetized data information by bartering or selling it by 2016.

When Big Data is monetized by selling it, it creates a new way of doing business and often changes the business model itself (Najjar & Kettinger, 2013).

This is supported by Iansiti & Lakhani (2014) who said that technology changes transform the two things a business model is defined by: the customer value proposition and way of value capturing. This is true from the value creation point of view in business models, where the basis for any business model is thought to be the company's core logic for creating and capturing value. (Shafer, Smith & Linder, 2005).

Internet of things is still relatively new, as it started trending in about 2014 (Google Trends, 2020), and the appearance of the devices is even newer. So, the academic marketing research about different business models is still at its early stages. The studies focus on IoT business models as a whole, so a standpoint of big data centric models could be beneficial as it might bring more specific information.

There is a lot of research on big data applications but there is still a lack of research on how companies providing big data solutions create and capture value from big data applications (Urbinati, Bogers, Chiesa & Frattini, 2019). Additionally, big data offerings haven't gotten much attention in the academic literature and the literature in big data value often takes the perspective of the company producing it and addresses the value for the company possessing it (Parvinen, Pöyry, Gustafsson, Laitila & Rossi, 2020). Also, Hanafizadeh and Harati Nik (2020) made a comprehensive literature review on data monetization and voiced a need for research that study data monetization in context of IoT. This research will contribute to this demand by studying selling data with IoT acting as a way of collecting big data for the customer.

As a customer value proposition is a core element for a business model, the value here being the data, it is beneficial also to study about the value of the sold data, which is created through big data management and analytics. Even if the data itself is worth something, managing and analysing only further increases the value. (Liang yu, An, Yang, Fu & Zhao, 2018). Also, value is often thought to be found within the characteristics of big data, most commonly used ones being volume, variety and velocity (Liang et al., 2018). The new context of IoT gathered data could also provide new insights of the characteristics of valuable big data and add to the value conversation. It is also interesting to find out how IoT changes the value creation process of big data.

## 1.2 Study objectives and research questions

This research will contribute to both the academic and business world. The purpose of this study is to add to existing research on big data value creation and value capturing in context of IoT. This research can also benefit IoT business model research overall by seeing if the results support current academic business model knowledge. Additionally, it seeks to uncover and understand valuable data and how it is processed to become that. For the business world this research can contribute by helping organizations to understand better how companies use IoT and big data to their benefit. Additionally, researching what kind of data is thought to be valuable to sell can help companies to evaluate if they have a good value proposition in their data.

Main research question:

- What kinds of business models do companies use for value capture with big data solutions when the data is collected from IoT devices?

Additional research questions:

1. What kind of big data is considered to be valuable for the customer?
2. How is big data value created and how does IoT change the value creation and capture of big data?

The research is conducted in Finland with companies operating here and the context is business-to-business (b-to-b) companies from the seller's point of view.

## 1.3 Study structure

To find answers to the research questions, this study relies on literature review and qualitative research. The structure is following: first there is a theoretical approach to the subject, then the research methodology and data are explained, after which research findings are presented and finally conclusions are drawn. The literature review consists of defining and characterizing Big Data and IoT, going through their value creation and finally discussing about their value capture in terms of business models.

To be on top of things, to better understand the subject and to help with lack of prior academic studies on the subject, this study will also examine industry research for example whitepapers and online articles. Moreover, resent studies, 2015 -2020, will be the main source of reference while the quick IoT development changes the life cycle of business models and services (Glova, Sabola & Vajdaa, 2014).

The theory literature review is followed by qualitative research. The empirical evidence is acquired by conducting six one-to-one semi-structured interviews. The interviewees are chosen from b-to-b companies that operate in Finland. They should be involved with the companies' data offering or otherwise well informed about the business model. Selling big data from IoT solutions doesn't have to be the main business of the firm, as long as the offering has a thought-out business model. An example of this could be a machinery organization that focuses on selling machines but also offer an IoT solution that gathers data of the machines to better be able to maintain it.

The interviews are recorded, and the recordings are transcribed resulting in over 40 pages of material. The study data is analysed with a thematic analysing method and the knowledge of the findings is scrutinized through a theoretical framework that the literature review has provided.

The results of this study reveal that information that can be used to predict the future or model the world around us is considered valuable. IoT provides real time data which can help to prevent value loss in data collection and processing latency. IoT itself is largely seen as a means of collecting data but it also helps by simplifying and making the value creation of the data and its processing easier. The companies see that their big data offering is more valuable than just the value of the data, it is seen as a solution to their customers' problems. With the offer, in addition to serving value to their customers, they want to support sales of the company's main business. To offer this value they opt to use service business models and they identified their business model to be SaaS (Software as a Service). Another interesting finding is that in larger companies where big data is not the company's main source of revenue, IoT is used to provide new digital functions and services to the existing product. On the other hand, smaller companies where service is their main source of revenue, focus on selling sensor data or digital services where IoT components are part of the service price.

# 2 THEORETICAL BACKGROUND

The theory background consists of value creation and capture theory. First an understanding of big data and IoT are made after which their value and its creation are examined. Then value capture is studied focusing on the business model theory of big data monetization and IoT. Finally, the theory is summarized and brought together to form a theory framework, that this study is based on.

## 2.1 Big Data

No one goes just for a run now. No, you track your run with your fitness tracker and smart watch. Otherwise, how would even know if you had a good run? You send texts, chat messages and e-mails instead of talking face to face. Soon, instead of keys, you use your smart phone to unlock your doors. This already is an option besides a traditional lock. Every time something like this happens, it leaves a digital footprint, data, behind. All this data is gathered and together it forms Big Data.

Big data consists of vast amounts of data. It is thought to be a consequence of digitalization as many digital activities are recorded (Faroukhi et al., 2020). The data can be generated internally, from public or it can be bought, and it can be both structured (such as dates, location) or unstructured (video, audio etc.) (Grover, Chiang, Liang & Zhang, 2018; Liang, 2018). Data, especially unstructured data, doesn't necessarily give any insights before it is mined into knowledge.

The insights generated can for example describe an event from its primitive elements. These elements are the 5W+H narratives: who, what, when, where, why and how. (Pigni, Piccoli & Watson, 2016.) This basically means that during a payment transaction big data can capture who is buying, what they are buying (E.g., chocolate bar), when this happens (5.10.2020 13.53), where (Koivistonkylä Prisma) and how (with a debit card). However, the why element, is often left in the dark (Pigni et al., 2016). In the example the motive for buying chocolate could be that it is a present for someone, she was hungry, or she just had a craving for sweets. Although, with the help of linking different data streams that seem unconnected at first glance, the why -element can be better guessed (Pigni et al., 2016). The subject could have posted on social media that she was having a craving for chocolate and so the motive can be guessed more correctly. So, the data with the right analysing can give important insights from different connections that aren't necessarily visible at first.

There are characteristics that define big data and sets it apart from just data. Most commonly they are referred as the 3Vs: Volume (the amount of data), Variety (the diversity of data formats) and Velocity (the speed of data) (Grover et al., 2018; Johnson, Friend, & Lee, 2017). However, the number of characteristics is often increased to 5 or 7 Vs which most commonly are Veracity (how true the data is), Value (the benefit of data), Variability (data that's meaning is changing) and Visualization (interpretation of data) (Ali-Ud-Din Khan, Uddin & Gupta, 2014; Faroukhi et al., 2020; Grover et al., 2018; Sathi, 2012). Also, Validity (the correctness of data for a specific purpose), Viscosity (the delay of data from source to destination), Volatility (the expiration of data) and Virality (speed of data spreading in a network) are used in characterizing the big data (Ali-Ud-Din Khan et al., 2014; Ge, Bangui, & Buhnova, 2018; Manogaran, Thota, Lopez, Vijayakumar, Abbas & Sundarsekar, 2017). In the end 11 different characteristics were found from various resources. Each of the characteristics don't have a one common definition. To further understand each characteristic, in table 1 they are described in more detail, bringing forward various definitions. The characteristics are important to understand to be able to extract value of big data analysing, which is a hoped result (Ali-Ud-Din Khan et al., 2014).

| Characteristic | Description |
|---|---|
| Volume | Refers to the huge size of data (Liang et al., 2018). |
| Variety | Data comes in diverse formats for example: text, sound video (Sathi, 2012). It can be structured or unstructured (Liang et al., 2018). |
| Velocity | "*…the speed at which the firm processes and analyzes customer data*" (Johnson et al., 2017)<br><br>"*Velocity is the characteristic of how rapidly the data stream is changing and being generated. Multiple data sources constantly generate data such that big data has an unbelievably high refresh rate.*" (Liang et al., 2018)<br><br>Velocity consists of throughput of data (the speed of data created) and data latency (how fast it can be analysed) (Sathi, 2012). |
| Veracity | "*Veracity represents both the credibility of the data source as well as the suitability of the data for the target audience.*" (Sathi, 2012)<br><br>"*Veracity refers to biases, noise, and abnormality in data. It is concerned with uncertainty, unreliability, or inaccuracy of data.*" (Grover et al., 2018)<br><br>Truthfulness of data (Ali-Ud-Din Khan et al., 2014) |

| | |
|---|---|
| Value | Is created by variety, velocity and volume (Liang et al., 2018).<br><br>*"It refers to the information and insights that data provides"* (Faroukhi et al., 2020) |
| Variability | *"It is different from variety; it refers to data whose meaning is constantly changing."* (Faroukhi et al., 2020)<br><br>Context of data (Ge et al., 2018) |
| Visualization | *"Is the process of illustrating relationships within large amounts of complex data in readable manner."* (Faroukhi et al., 2020) |
| Validity | Similar concept to Veracity. The same data can be valid for a certain use but not for another. *"the correctness and accuracy of data with regard to the intended usage measures the speed at which data can spread through a network."* (Ali-Ud-Din Khan et al., 2014)<br><br>Correct processing of the data (Ge et al., 2018) |
| Volatility | The retention policy of data (Ali-Ud-Din Khan et al., 2014)<br><br>At some point the data becomes irrelevant. So, it should be considered when this happens and get rid of it after, so the amount of data doesn't become too overwhelming (Firican, 2017). |
| Viscosity | *"Element of velocity and represents the latency or lag time in data transmit between the source and destination"* (Manogaran et al., 2017) |
| Virality | *"Represents the speed of the data send and receives from various sources"* (Manogaran et al., 2017)<br><br>*"Measures the speed at which data can spread through a network." (Big Data Alliance, 2020)* |

Table 1: Characteristics of big data

## 2.2 Internet of things

The term Internet of things was first coined by Kevin Ashton in 1999 for using radio frequency to interconnect objects (Ashton, 2009; Suppatvech, Godsell & Day, 2019). Even though the internet of things has become commonly used term since then, there seems to be no official or standard definition of it or even a common understanding of everything it includes (Wortmann & Fluchter, 2015). For example, Dijkman, Sprenkels, Peeters, & Janssen (2015) defined it as "*the interconnection of physical objects, by equipping them with sensors, actuators and a means to connect to the Internet.*" Whereas Femminella, Pergolesi and Reali (2018) said "*...it* (IoT) *essentially consists of the interconnection of devices, having one or more network interfaces, which deliver information about their status, whatever meaning the concept of status is given.".*

Some definitions emphasise thing that are being connected; others emphasise connectivity aspects (Wortmann & Fluchter, 2015). It appears that others state internet as the connectivity when others don't specify the type of connectivity. Often the word "network" is used when talking about connectivity parts of IoT. However, network doesn't equal internet: network connects computers that can share information with each other that is often owned by someone, when internet connects multiple networks and is open for everyone (TechDifferences, 2019). The connectivity doesn't stop with devices either. IoT can interconnect people, environments, virtual objects and industrial equipment (Attaran, 2017). Attaran (2017) also states that IoT basically connects anything, to anyone, at any time, in any place, service or network. In conclusion it can be said that the connectivity doesn't have to be through internet even though the name *internet* of things might so suggest. However, according to Porter & Heppelmann (2014) connectivity is not what makes IoT profoundly different, what does is the transformation of the things and the increased capabilities of the products and data generated.

In summarizing there are three core elements to IoT: physical components, smart components, and connectivity components which form a cycle of value: smart components strengthen capabilities of physical components, connectivity increases value of smart components and physical product enables the others to exist as the other parts enable value to exist outside the physical component (Porter & Heppelmann, 2014). Diving a bit further into the construction of IoT can help to understand the concept better. The general architecture consists of a physical layer, network and communication layer, data centre layer, service layer and application layer and data flows through each of them (Niyato et al., 2016a). In Figure 1 below we can see the architecture visualized.

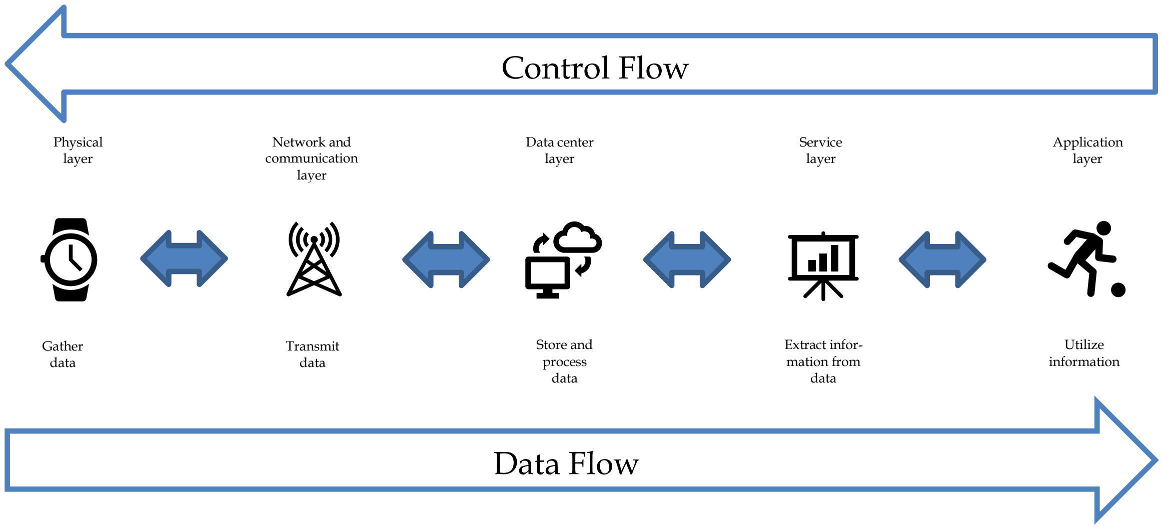


Figure 1: General architecture of an IoT system (Niyato et al., 2016b)

## 2.3 Value creation

Value creation is the goal of any rational organization, so they try to understand what customers value and try to provide that value for them (Faroukhi et al., 2020; O'Cass & Ngo, 2011).

Value can be perceived use value that the customers subjectively define by the usefulness of the product/service for them or exchange value that is realized in the buying transaction in terms of money (Bowman & Ambrosini, 2000). Perceived value comes from the notion that customers can only give value to things they perceive themselves (Bowman & Ambrosini, 2000). However, it is the companies' job to explore, interpret and deliver that value based on what they believe the customers perceive as valuable (O'Cass & Ngo, 2011).

Resource itself doesn't bring any new use value to the firm before it has been worked on. So, the actions of the firm give new use value and it's true with information like big data too. (Bowman & Ambrosini, 2000.)

### 2.3.1 Big data value creation

Maximum value is a sought for result of data processing (Ali-Ud-Din Khan et al., 2014). Generally, the value of big data is created through big data management and analytics. Even if the data set itself is worth something, managing and analysing only further increases the value. (Liang et al., 2018.) However, analytics is not the only important part of big data value creation, it needs more steps, a chain of events.

Faroukhi et al. (2020) researched the evolution of data value chains and presented a big data value chain (figure 2) that reflects research findings. The chain has seven links: Data generation, Data acquisition, Data pre-processing, Data storage, Data analysis, Data visualization and Data exposition.


Figure 2: Big data value chain (Faroukhi et al., 2020)

Generating data has to with how the data was created, for example where is the source of it and was it created intentionally. Data acquisition is more about obtaining the data from the source. (Faroukhi et al., 2020.)

The data should be pre-processed before it goes to storage as it may be too noisy and to help with the further analysing (Faroukhi et al., 2020). With pre-processing data is prepared. There are some scholars that think this is the most important part in the analytics (see: Rehman, Chang, Batool & Wah, 2016). The quality of data is being improved by different methods for example to reduce noise, detect outliers, remove anomalies and connecting data from different sources (Rehman et al., 2016).

The value of storing should not be overlooked either as it affects the workings of the later aspects. Value storing also entails the management of large datasets which can provide difficulties (Faroukhi et al., 2020). One should be aware of the costs of storage as the value of the resulting knowledge should exceed the costs of the data management (Ali-Ud-Din Khan et al., 2014).

Data analysing has perhaps generated the most interest and research. It is often used to describe the pre-processing parts too. Different analytic tools and human talent are used to inspect and mine data to find value in term of useful insights in it (Faroukhi et al., 2020; Grover et al., 2018; Elia, Polimeno, Solazzo, & Passiante, 2020). Analysing data into insights also entails the modelling and interpretation of data (Ge et al., 2018). The combination of insights is important as the value is dependent on it (Grover et al., 2018).

After analytics data visualization is next in the big data value chain. It can show hidden patterns in the data and helps to represent the insights in more universally and comprehensively (Faroukhi et al., 2020).

The last link to the chain, data exposition has to do with using the resulting knowledge, it can be either for personal use or trading it on. (Faroukhi et al., 2020.) This last part helps us to understand how this value chain also works with selling value to the customer not only for value inside the corporation.

Perfecting this chain is important as new data is generated rapidly which means that organizations need to be able to mine, analyse and translate that data into insights faster than before or their rivals (Johnson et al., 2017).

### 2.3.2 Big data value

Having good characteristics mentioned in chapter 2.1 can be a sign for valuable data. In addition, Davenport, Harris and Abney (2017 pp. 326-7) listed other characteristics that increase the value of data. The data should be correct, complete, current, consistent, in a context, controlled and analysed. The way the data is used and combined is also important (Parvinen et al., 2020).

One reason for why the value of big data is difficult to capture is that it's unique in a way that it might be expensive to collect but it is cheaply reusable, it can be integrated, and it's not consumed in a way we are used to assets being used, so traditional ways of asset evaluation isn't equipped to capture the value (Grover et al., 2018; Parvinen et al., 2020). In addition, data's value can lessen after it is initially utilized. What makes it even harder to define a value for data is that it depends on the context, situation and time and it is realized at the time of utilization. (Parvinen et al., 2020.)

### 2.3.3 IoT value creation

The benefits of IoT can be realized in a same way than in big data. Zhang & Yueb (2019) state that the advantage of IoT comes from extracting and mining the data. This makes sense as IoT devices collect data. As a result, it can be argued that IoT's value is somewhat intertwined with big data's value.

Fleisch, Weinberger and Wortmann (2015) introduced an internet of things value creation framework below (Figure 3). There are five layers: Physical thing, Sensor and Actuator, Connectivity, Analytics and Digital service. No level is independent. The value comes from integrating the digital world with the physical and it is more than the sum of levels.

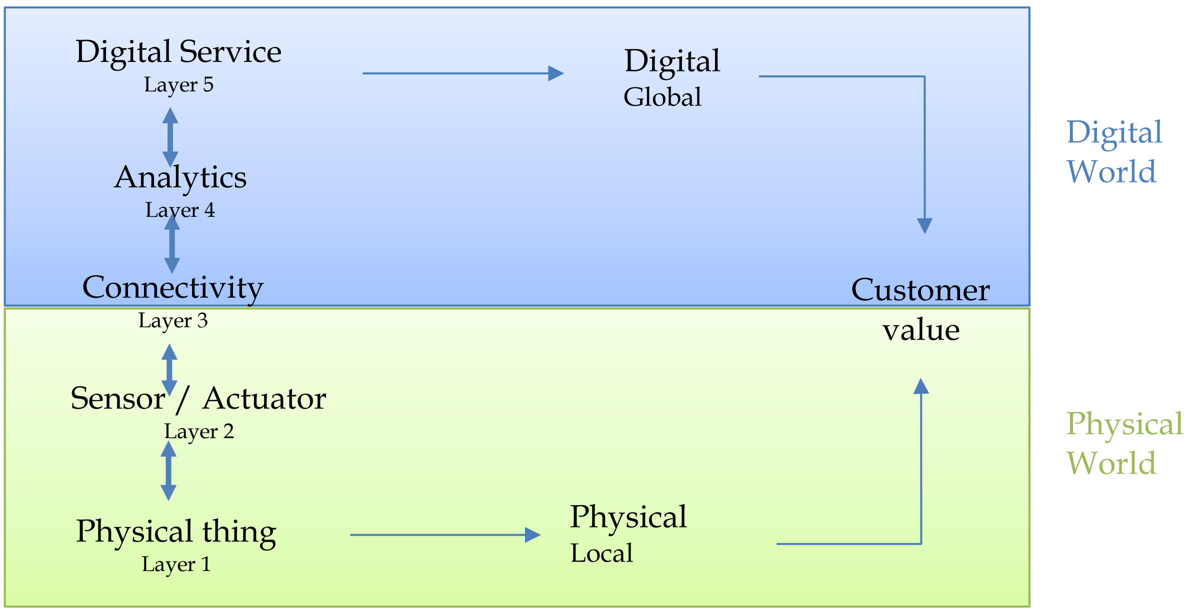


Figure 3: IoT value creation (Fleisch et al., 2015; Wortmann et al., 2020)

Fleisch, Weinberger and Wortmann (2015) also represented a more reduced abstract formula of the value creation for product service logic (Figure 4): IoT is a thing with an IT solution, such as hardware and software, that equals the value of the local and physical thing-based function plus an IT-based service, that can be digital or global. For example, car with an IoT function gives value of being able to move from one place to another but also has it-based service such as seeing the location of the car from an app.

| Thing | + | IT (Hardware / Software) | = | Thing-based Function (Physical / Local) | + | IT-based Service (Digital / Global) |
|---|---|---|---|---|---|---|
| Watch | + | IoT stack | = | Time | + | Emergency call |
| Heater | + | IoT stack | = | Heat | + | Cost savings |
| Bike | + | IoT stack | = | Ride | + | Fleet management |

Figure 4: IoT product service logic (Fleisch et al., 2015)

### 2.3.4 IoT value

Essentially an IoT object is both a sensor that produces big data, thus being a data source, and data transmitter (Femminella et al., 2018; Niyato, Hoang, Luong, Wang, Kim & Han, 2016b). IoT needs big data analytics to bring out good insights of the data (Ge et al., 2018). Therefore, the value of IoT itself might be hard to realize on its own.

There is a loss of data's value in delays in capture latency, analysis latency and decision latency (Pigni et al., 2016). In other words, the value of big data is increased if it is provided at the right time and place (Parvinen et al., 2020). IoT can solve this issue to a certain amount as it provides fast data retrieval. IoT is also associated with better quality data. (Attaran, 2017.) Moreover, IoT's real time data offers value with making the working of the physical aspects like a machine's performance more transparent and less uncertain (Ehret & Wirtz, 2017).

## 2.4 Value capture

Bowman & Ambrosini (2000) state a value capture is a realization of exchange value through customers and providers. Data monetization is a term used to describe this process of generating profit from data (Faroukhi et al., 2020; Hanafizadeh & Harati Nik, 2020). Najjar and Kettinger (2013) defined it as converting data's intangible value into real value or into other tangible benefits.

According to studies data monetization can be improving processes in an organization (Wixom & Ross, 2017), avoiding costs (Najjar & Kettinger, 2013) or tapping into untapped potential (Pigni et al., 2016). It is largely about new product development (Johnson et al., 2017), selling data (Najjar & Kettinger, 2013; Wixom & Ross, 2017) bartering or wrapping data information around an existing product (Wixom & Ross, 2017; Woerner & Wixom, 2015).

When Big Data is monetized by selling it, it creates a new way of doing business and often changes the business model itself (Najjar & Kettinger, 2013). This is supported by Iansiti & Lakhani (2014) who said that technology changes transform the two things a business model is defined by: the customer value proposition and way of value capturing. Furthermore, it is said that if a company wants to be a strategic player in the big data and IoT markets they should rethink their existing business model (Ju, Mi-Seon, & Jae-Hyeon, 2016).

Value proposition is essentially a product, or a service, provided by a company for a customer's value need (Muhtaroglu, Demir, Obali & Girgin, 2013). It is the core component in a business model, and it should present the customer the benefits they receive and how they exceed the cost (Niyato et al., 2016b).

### 2.4.1 Business models

Companies use business models to create and capture value from their data assets (Parvinen et al., 2020). Fundamentally business models are a way to achieve financial returns, which also applies to IoT (Dijkman et al., 2015). In fact, it is seen unlikely to gain profit without a clear business model (Chan, 2015).

The basis for any business model is the company's core logic for creating and capturing value (Shafer et al., 2005). A business model defines how a company does business, linked activities that tell the way how specifically they satisfy their stakeholders needs (Amit & Zott, 2012). According to Glova et al. (2014) the most used definition of a business model is by Timmers (1998):

> "*An architecture for the product, service and information flows, including a description of the various business actors and their roles; and A description of the potential benefits for the various business actors; and A description of the sources of revenues*."

However, there is no one determined definition in the academic world (Glova et al., 2014). There is a more value centric definition by Osterwalder, Pigneur, & Tucci (2005):

> "*A business model is a conceptual tool that contains a set of elements and their relationships and allows expressing the business logic of a specific firm. It is a description of the value a company offers to one or several segments of customers and of the architecture of the firm and its network of partners for creating, marketing, and delivering this value and relationship capital, to generate profitable and sustainable revenue streams*".

### 2.4.2 Big data monetization business models

In their systematic literature review, Faroukhi et al. (2020) summarized that big data monetization can be divided by four main axes:

*"(i) Data extracted from customers' activities which could be in its raw format. (ii) Data providers that collect and sale primary and secondary data. (iii) Data aggregators that provide customers with aggregated services. (iv) Technical platforms, based on infrastructure, analysis, computing and cloud capabilities that enable to process, consume and share data"*

Parvinen et al. (2020) identified business model variations for big data monetizing via customer and offering type. The types of customers are current customers, actors in the current value chain and anyone interested to buy, the latter having the most possible customers. They base the offering types on Van't Spijker's (2014) and Thomas & Leiponen's (2016) findings and they are: directly selling data, providing insights and creating a scalable service. The level of refinement scales along with the types, the latter being the most refined. Together they create nine business model types (table 2). The first step is often selling data to current customers. The third customer type, offering to anyone, is the riskiest and therefore one should go first through the paths of offering to current customers and actors in the current value chain.

Amount of customers

Level of refinement

| Customer of monetization / offering | **Providing to current customers** | **Providing to actors in current value chain** | **Providing openly to anyone** |
|---|---|---|---|
| **Selling data** | Sell aggregated data to current customers as an additional feature | Sell aggregated data considering end-users to current suppliers | Sell aggregated data on market activity to investors and authorities |
| **Providing insights** | Provide insights to current customers considering their business environment | Provide trend and demand insights to suppliers | Provide analysis of consumer demand to investors |
| **Creating a scalable service** | Provide a service, where customers receive information of business environment | Provide a service, where suppliers can analyse end-user consumption information | Provide a service, where investors can access the real-time information considering market trends |

Table 2: Business model variations for data monetization (Parvinen et al., 2020)

### 2.4.3 IoT business models

According to Wortmann et al. (2020) old, more traditional firm-centric business models don't work with IoT because IoT is a disruptive force. As result of interconnected nature of IoT, firms need to collaborate more across industries or even with competitors. This presents its own difficulties in building new business models. (Chan, 2015; Ju et al., 2016.)

Overall, the focus in IoT business model theory is on service business models rather than in product business models, which a trend seen in IT (Reen, Hellström, Perminova-Harikoski & Wikström, 2017). Fleisch, Weinberger & Wortmann (2014) support this idea with their notion of how IT-influenced business model patterns follow three trends: integration of users and customers in their value creation chain, service orientation, and core competence analysis, where customer use data collected and analysed.

Fleisch et al., (2015) presented different business model patterns that fit with IoT:

1. Physical freemium: a free digital service with a paid for physical thing.
2. Digital add-on: low margin physical thing, where the idea is that digital services are bought with higher margins.
3. Digital lock-in: only the original seller's additional components fit with the product limiting for example counterfeits.
4. Product as a point of sales: the product is a place of digital sales such as a smart phone.
5. Object self-service: the object can monitor itself and alert to issues.
6. Remote usage and condition monitoring: the smart thing transmits data about itself which allow better monitoring. This allows for example pay per use models.
7. Digitally charged products: basically, what IoT is all about, charging a product with sensor based digital services and new value propositions.
8. Sensor as a service: the focus is on the sensor data unlike in digitally charged product where the focus is on the services.

Since then, the patterns have been redefined further. For example, Suppatvech, Godsell & Day, (2019) identified four archetypes of IoT enabled business models based on their main value proposition from their literature analysis. They are add-on, sharing, usage-based and solution-oriented with nine subcategories.

1. Add-on: IoT is used to provide additional functions or services to the existing offering. There are four different types: innovative digital services creating a hybrid offering, facilitate service provision, leverage customer data, and on-demand provision.
2. Sharing: the customer can use/access the product or a certain amount of time when another customer can use at another point in time.
3. Usage based: basically, a subscription model with different options to choose from based on the need or a pay per use model where the customer pays based on the consumption.
4. Solution oriented: availability for the product or optimisation of the customers operations.

Add on business model has had the most attention in academic research, also early on from Fleisch et al.'s (2015) work. This makes sense as according to Suppatvech et al. (2019) it is also the most common model used in practice, the second most used model being solution oriented.

Fleisch et al. (2015) continued their work with IoT business models patterns and identified nine different IoT business models. These IoT business models by Wortmann et al. (2020) are characterized by where the value creation happens (is it physical or digital) and by the type of value delivery (is it a product or a service).

According to them, there are direct (involves two parties) and indirect (ecosystems with 2+ parties) business models for IoT. The models also vary between single and dual stream (source of revenue) patterns.

Direct single stream patterns where there is one-time payment and additional aspects are offered for free:

1. Physical product: the IoT device is bought, and the data is received for free.
2. Hardware as a service: IoT devices are rented, and the digital service is for free.
3. Digital service: digital service is paid for and the customer is provided for hardware without a cost.

Direct dual stream patterns where both physical and digital product are paid for either directly along each other or as after-sales are:

1. Digital add-on: Main or better digital aspects are bought separately from the IoT device. Some aspects digital can be offered for free.
2. Physical freemium: different subscription model options that are needed to really benefit from the IoT part of the device. There might be minor additional free aspects.
3. Service bundle: different services for the IoT device can be bought, for example an automated maintenance. The device can be bought and used without the benefits of the IoT, unless service is bought that allows the smart and connectivity components to be used.

Based on their research cases 56% of the companies using direct revenue models are using a version of physical product model and 25% use the physical freemium model. However, it is good to note that potential service revenue is unrealized with the physical model.

Indirect revenue models exist in ecosystems where the situation is win-win for the provider, customer and third parties. The involvement of third parties grows with the complexity of the model.

1. Complimentary offer: third parties offer complementary services or products for the IoT solution.
2. Granting access: third parties can be allowed an access for the IoT device in exchange for incentives, e.g., money.
3. IoT for free: the customer gets the IoT solution for free and third parties can access it and essentially pay for it.

IoT service business models by Leminen, Rajahonka, Westerlund & Wendelin (2018) focus more on the ecosystems which are, according to research, needed beside the firm centric models because of IoT's more collaborative nature (Chan, 2015; Ju et al., 2016; Wortmann et al., 2020). In their theoretical framework of service business models, the business models are divided by their ecosystem's hierarchy and the standardization of the service. Leminen et al. (2018) identified four types of theoretical service business models. The types are value chain efficiency, industry collaboration, horizontal market and platform as seen in table 3.

| ECOSYSTEM | Standard | Context-sensitive |
|---|---|---|
| Heterarchical open | 2<br>Industry collaboration | 3<br>Horizontal market |
| Hierarchical closed | 1<br>Value chain efficiency | 4<br>Platform |
| | SERVICE | |

Table 3: A theoretical framework for classifying IoT business models (Leminen et al., 2018)

In the table, the number one, value chain efficiency, is a standardized, single purpose service in a closed hierarchical ecosystem for a customer. The goal is to improve efficiency and reduce costs per supply chain. In number two, industry collaboration, standardized single purpose services per industry are in an open heterarchical ecosystem. One company might have multiple services, and some industries such as healthcare, need this kind of openness to IoT standards and solutions. Number three, horizontal market, is heterarchical open ecosystem that has context-sensitive applications. Services are often based on re-using sensor data in a new way. Lastly in number four, platform, a transformed horizontal market where there is a dominant platform player who acts as a resource integrator. Other players are partners that use the platform to create IoT applications which are offered in the platform.

## 2.5 Research framework

This chapter summarizes the key theoretical background used in this study and a theoretical framework is formed.

Companies' target is to create and provide value to the customer, so understanding what customers value is essential (Faroukhi et al., 2020; O'Cass & Ngo, 2011). This is also true with big data, as it is seen as a tradeable resource (Niyato et al., 2016a) and companies want to use it to create revenue (Woerner & Wixom, 2015). Therefore, understanding what customers see as valuable in big data is important. This is considered with additional research question *What kind of big data is considered to be valuable for the customer?*

Value can be found within the characteristics of big data, most commonly used ones being volume, variety and velocity (Liang et al., 2018). Other characteristics of data are veracity, variability, visualization (Ali-Ud-Din Khan et al., 2014; Faroukhi et al., 2020; Grover et al., 2018; Sathi, 2012). Also, validity, viscosity, volatility and virality are used in describing the big data (Ali-Ud-Din Khan et al., 2014; Ge et al., 2018; Manogaran et al., 2017). Other qualities that increase the value of data are correctness and completeness, it should be current, consistent and be in a context, controlled and analysed. (Davenport et al., 2017 pp. 326-7)

The value of big data is created through big data management and analytics. Even if the dataset itself is worth something, managing and analysing only further increases the value. (Liang et al., 2018). Data processing's goal is to create maximum value (Ali-Ud-Din Khan et al., 2014). Faroukhi et al. (2020) presented a big data value chain of the process (figure 2). The chain has seven links: data generation, data acquisition, data pre-processing, data storage, data analysis, data visualization and data exposition. The value of big data is then created through data management and analytics that create a process. Research question *How is big data value created* further analyses the process.

Being able to analyse and use big data to one's advantage promises enhanced service for the customer, and profitability to the company (Farah, 2017). This active asset is also a new novel source of revenue that can give competitive capability to its owners when used right (Hanafizadeh & Harati Nik, 2020).

There are many ways to generate data and it can come in many different forms, structured and unstructured (Grover et al., 2018; Liang, 2018). Essentially an IoT object is both a sensor that produces big data, thus being a data source, and data transmitter (Femminella et al., 2018; Niyato et al., 2016b). The advantage of IoT comes from extracting and mining the data (Zhang & Yueb, 2019). IoT needs big data analytics to bring out good insights of the gathered data (Ge et al., 2018). IoT transforms things and increases capabilities of the products and the data generated (Porter & Heppelmann, 2014). Therefore, the value of IoT itself might be hard to realize on its own and need the aspect of big data with it. IoT also affects the value creation of the big data. Research question *How does IoT change the value creation?* observers further IoT's part in value creation.

Value capture is a realization of exchange value, financial returns, through customers and providers (Bowman & Ambrosini, 2000; Dijkman et al., 2015), and the basis for any business model is the company's core logic for creating and capturing value (Shafer et al., 2005) This applies to data assets and IoT too (Parvinen et al., 2020; Dijkman et al., 2015).

When Big Data is monetized by selling it, it creates a new way of doing business and often changes the business model itself (Najjar & Kettinger, 2013). Organizations have also recognized IoT as a new up and coming game changer that is thought to disrupt existing business models (Wortmann et al., 2020).
Research questions *How does IoT change value capture of big data?* and *What kinds of business models do companies use for value capture with big data solutions when the data is collected from IoT devices?* dive into these aspects.

So, what kind of big data is valuable affects the value proposition which in turn affects the value creation and capture. If the value creation is changed, then the value capture might change too. In addition, IoT can influence the value proposition, creation and capturing. This framework is explained in figure 5. Moreover, who owns the data is an important part of the business model as it is part of the value proposition.

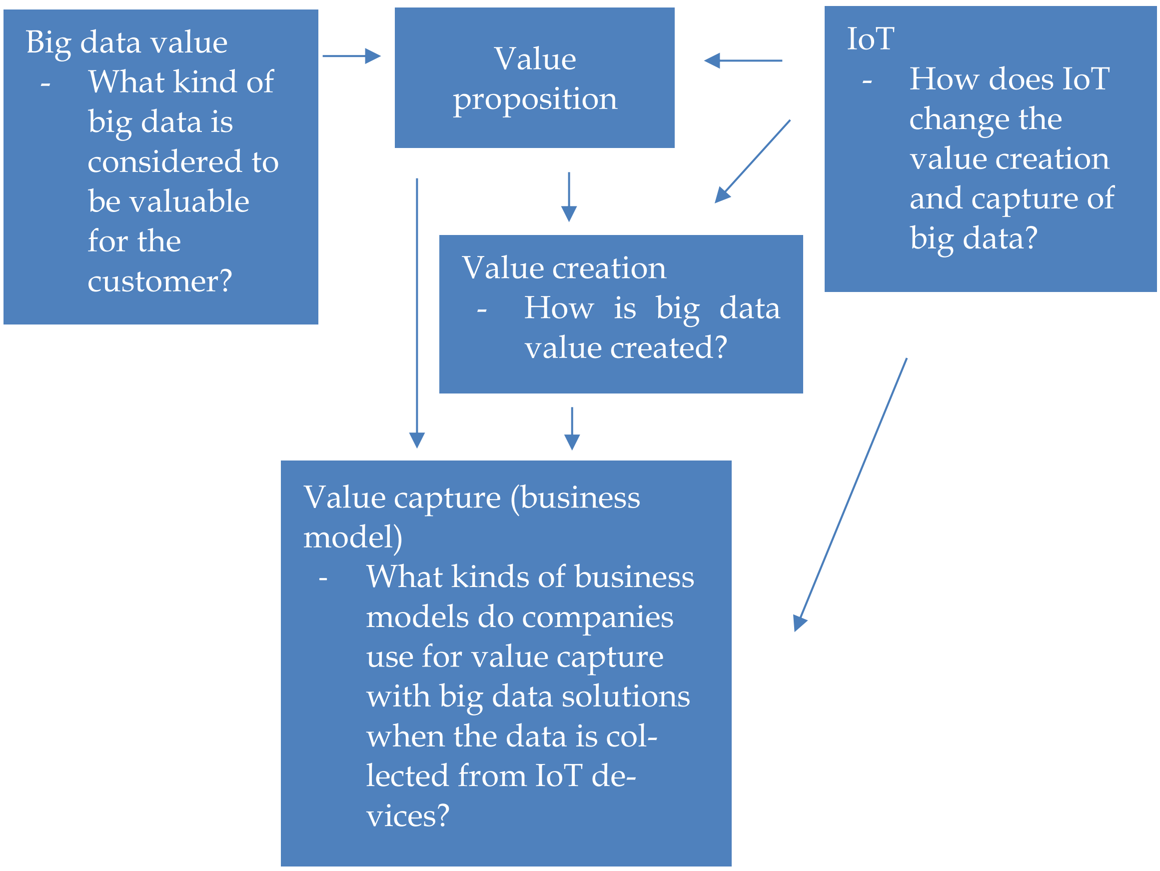


Figure 5: Research framework

# 3 DATA AND RESEARCH METHOD

In this chapter the methodological approach is introduced. First there is a general explanation of what methods were chosen after which the execution of the research is described. Furthermore, the data analysis methods are introduced.

## 3.1 Research method

This research is conducted with qualitative methods. It is generally agreed that qualitative research describes and further expands the understanding of the topic. It is exploratory, flexible and gives a holistic understanding of the topic. Qualitative study is also a good choice when the topic is fairly new and lacks structured understanding, which is needed in a good quality quantitative research. (Eriksson & Kovalainen, 2008.) Qualitative research was deemed to be a good fit as there is yet to be found a more structured understanding and this topic is somewhat new.

A thematic interview was chosen, where the interview follows certain beforehand decided themes (Eskola & Suoranta, 1998, p. 63; Tuomi & Sarajärvi, 2018, p. 65). The themes follow the most important topics and aspects of the research that are necessary to address to answer the research questions (Vilkka, 2021, p.99). This method works well for this study as it allows to refine and deepen the understanding based on the answers with additional questions, and it also allows changes in the order and scope of each theme (Eskola & Suoranta, 1998, p. 63; Tuomi & Sarajärvi, 2018, p. 65). The interviews are also semi-structured, where there are some basic questions thought out in advantage that would be asked from all of the interviewees. As thematic interviews are often semi-structured it provides more freedom than structured interview to capture important information, but the interviewer has more control to steer the interview than in unstructured interview (Walle, 2015). Structured interviews are more suited for quantitative studies and they often limit the answers with predefined questions (Yin, 2016, p. 141). These close-ended questions were tried to be avoided and instead open-ended questions, that promote participant to engage in the topic more and use their own words, were used (Yin, 2016, p. 143).

## 3.2 Data collection

The sampling method chosen for this study was purposive sampling. With that the researcher makes their own judgement and deliberately chooses the interviewees that they think can give plentiful and relevant information of the subject. To maximize information, the subjects should vary between each other that might result in opposing views of the topic. (Yin, 2016, pp. 93-94.) Along with purposive sampling, convenience and snowball sampling methods were used. The researcher had some common friends with the interviewees, which made getting their contact information and agreeing on an interview easier, so some of the sampling was done by convenience methods. Some of the contacted people offered company names that they thought would suite this study. This fitted with snowball sampling where new subject leads branch out from old ones (Yin, 2016, p. 95).

The researcher did research into the offering before contacting to determine if the offering would fit into the description: a b-to-b product, that sells big data or insights of it and the data has been collected with the help of an IoT solution. When needed, the offering was discussed further on the phone when contacting the companies. Selling big data from IoT solutions doesn't have to be the main business of the firm, as long as the offering has a thought-out business model. Also, the companies should operate in Finland.

Different industries and different types of offerings were purposefully looked for to better understand the subject as a whole. For example, the companies had a different level of IoT usage and one of the offerings was still in the development phase. In the end, ten companies were contacted of which one didn't reply and three were deemed not to be the best fit after all, resulting in six separate interviews. In table 4 the interviewed companies are named, its industry and size (from options: small, medium, large) are described. The companies that offer the solutions as the main product are also marked. One of the companies is a subsidiary of a larger firm but it is be analysed as a separate entity.

| Company | Industry of the company | Company's size | IoT/big data offering is the main business |
|---|---|---|---|
| Company A | Building maintenance | Large | |
| Company B | Sport's analytics | Small | X |
| Company C | Logistics | Large | |
| Company D | Logistics and supply chain | Small | X |
| Company E | Industrial automation solutions | Large | |
| Company F | Heavy machinery | Large | |

Table 4: Interviewed companies

The interviewees were chosen based on their knowledge of the subject. They should be involved with the companies' data offering or otherwise well informed about the business model. They were presented with a summary of the subjects that were to be discussed and asked if they thought they were able to answer them well. In some cases, the researcher's friend who worked at the interviewed firm did the initial evaluation of a person who would suite to answer the questions. The interviewees were also presented a privacy notice.

All interviews were conducted remotely with a secured Zoom-meeting which were recorded with the permission of the interviewee. Most of the interviews were during the first week of January 2021. They lasted from about 30 minutes to an hour and were mostly held in English. The interviewees were given the option to choose from English and Finnish. While the interviewees were Finnish speaking, they might use English as a working language in an international company and so be more used to talking about the subject in English rather than in Finnish. Also considering this research, English interviews were considered being better for not to lose any meaning in the translation from Finnish to English. Table 5 presents information of the interviews: the interviewee's position in the company (from options employee, management, and senior management), interview's date, duration, and language.

| Company | Interviewee's position in the company | Date of the interview | Duration of the interview | Language of the interview |
|---|---|---|---|---|
| Company A | Management | 17.12.2020 | 1 h 11 minutes | English |
| Company B | Senior management | 5.1.2021 | 35 minutes | Finnish |
| Company C | Management | 7.1.2021 | 42 minutes | English |
| Company D | Management | 7.1.2021 | 44 minutes | English |
| Company E | Management | 7.1.2021 | 37 minutes | Finnish |
| Company F | Management | 8.1.2021 | 1 hour | English |

Table 5: Interview information

The interview questions were created with the research questions and theory background in mind. Each question's suitability was thought over by considering *To which research question does this answer?*. It was made sure that every research question had at least one corresponding predefined question in the interview.

The questions were divided into themes. First background questions, such as describing the role of the interviewee, were asked, after which came value proposition questions. In value proposition the interviewees described what is generally valuable data and what added value does IoT bring to the big data. These questions worked also as a warmup to the topic at hand. The offer was discussed also to understand it better and to figure out why do the customers want to buy the offering and to better understand their value creation and capturing. Value proposition theme was followed by value creation. In it, questions were asked to figure out the value creation of the offer, especially how the big data is processed and analysed as well as the IoT's role in it. Lastly in value capture theme the customer groups and different aspects of their business model, such as standardization, were asked. Also, subjects of the ownership of the data and uniqueness of the business model and offering were touched.

The course of the interview tried to follow the order of the presented themes in the scripted questions as they were thought out to be in a natural order for the interviewees, which is a goal in thematic interviews (Vilkka, 2021, p. 99). However, the researcher asked multiple off script additional questions to make sure she understood the subjects at hand correctly and to gather more information of the initial question if the initial answer wasn't satisfying enough. Also, if the interviewee talked about an issue related to a future question, exceptions were made to the order. At the end of some of the interviews, there was a small conversation of the issues at hand and further clarifying questions were asked. Some of the interviewees even showed glimpse of the user interface or shared further knowledge that wasn't to be recorded but helped the researcher to understand the offer.

## 3.3 Data analysis

Recording made transcribing and therefore a more detailed analysis possible. The transcription was done in an edited manner as the content of the conversation is more important to this research than the way it was said. Every word was typed out, such as repetitions of the same word or stutters, mostly correctly spelled ignoring possible dialect. Strong emotions were typed out such as "laughter" and clear interjections like Umm… were transcribed. However, interrupted words were not taken into account nor pauses' lengths were measured. To maintain confidentiality, the company's name and distinguishable product names were coded out as **company X*, and **company X product*. The transcripts don't mention any of the interviewees' names either. The transcriptions of the interviews resulted in over 42 pages of material.

In the findings, there are quotes of the interviews to support the claims and to better explain them. In them, some of the grammatical mistakes have been corrected, filler words or mannerisms such as *like* as well as repetitive words have been deleted. The quotes in general have been modified in a way that makes sense as a readable extract of the conversation, with the least amount of modification, to help the reader understand better what was being said. There are a few texts in brackets to give additional explanation. If the quote has been translated, there is a notion of that.

After the transcription and initial overview of the material, the data was compiled into one document since in qualitative research the material is often scrutinized as a whole (Alasuutari, 2012, p. 29). Then the material was disassembled and reassembled with different analysis. In thematic analysis the most relevant themes of the material regarding the research questions were analysed. The analysis started with the interview themes: value proposition, creating and capturing that follow the research background. The attention was in what is said about each theme. (Tuomi & Sarajärvi, 2018, p. 79, 125.) After which the material was typed into categories by finding similarities (Eskola & Suoranta, 1998, p. 130) and then the content was broken down by, for example stating how many times a certain result was found, which helps in spotting patterns (Yin, 2016, p. 184). Found categories followed the scripted questions. The categories were: generally valuable data and IoT's value, how is the big data processed and analysed, and what role does IoT play in the value creation process. Categories involving business models were: what do the customers primarily pay for, why do they have their offering, do the interviewees believe their offer is unique, business model in general, what are the customer groups, is there additional services or aspects in the offer, is the service standard for different customers, the business model's uniqueness and finally who is the owner of the data.

In the end six themes emerged from the analysis that follow the research questions:

1. Valuable big data and IoT
2. Data analysis
3. Process of data analysis
4. What role does IoT have in the value creation process?
5. Companies' value capture and business models
6. Who owns the data?

# 4 RESEARCH FINDINS

In this chapter, the findings of this study are presented after which they are discussed further. The findings are divided into three major sections that are in line with the research questions and the emerged themes from the research data analysis. In valuable data and IoT, findings for research question *What kind of big data is considered to be valuable for the customer?* are explored. In data analysis, the data analysis process insights are discovered in response of research question *How is big data value created and how does IoT change the value creation and capture big data?*. Finally, the offerings and business models of the companies are investigated for the main research question *What kinds of business models do companies use for value capture with big data solutions when the data is collected from IoT devices?*

## 4.1 Valuable data and IoT

Data can be valuable in multiple ways to an organization, such as more knowledgeable decision making or better understanding of their customers, but not all valuable data within a company will be valuable for the customer.

In general, the interviewees thought valuable data to buy, or sell is data that can bring added value. Value bringing data was considered to be data that is actionable, "*data that they can base their decisions on. Or even start to do the actions automatically not even requiring human intervention between data and action*." Data was also thought to be valuable when it is all comprehensive, allows predictions of the future based on history, and can be used to model the surrounding world or make trends. This kind of valuable data can also give a better understanding of the customer's own company by understanding it through the numbers thought one manager.

*"Everyone, with this kind of data, would like to go into this direction that we could already estimate for example, some faults before they happen. That's sort of the Holy Grail that everyone wants to be able to save some things before they break and it does make the customer's life a bit easier and better, but that's actually quite hard to make in practice."* Company C

Interviewees from companies having something to do with manufacturing industry were more focused on how data value can have monetary benefits by helping the customer to develop a system in a way that has economic gain such as cutting down costs.

"(valuable data) *can enhance your business or sort of raise your productivity and especially cut down unnecessary costs."* Company C

*"That (*beneficial data*) is something that has to serve their business, and to give help to develop the system whatsoever or lead straight to the benefit monetarywise etc."* Company F

No one questioned whether there would not be any value in data. One of the interviewees said *"Basically, any sort of data is valuable for just someone in the world."*. When another thought whether the value of the data is yet even realized everywhere, in every industry, especially in the sport industry.

Industry specificness also came up with Manager F who wondered how their heavy machinery industry is more traditional and conservative, so changes such as digitalization, IoT and data happen slower.

Moreover, senior manager B pondered how the importance of data value is only rising with digitalization and when we realize how data can be used to provide different value-added services and unique opportunities.

Automated and real time information were referred the most as the added value that IoT brings to big data. Real time data allows faster reactions and automation reduces manual work, human error and can allow making adjustments to systems without a human intervention.

IoT was also thought to be a good way to gather data as it brings concreteness to the data, can give small individual technical statuses, and makes the accuracy better. IoT was also seen to be able to give *actual facts* to its users.

## 4.2 Data analysis

Data analysis is used to realize the value that data can give (Elia et al., 2020) and the findings suggest that having IoT makes the data analysing process easier. Manager A said that with IoT, they usually already know what the data has been measuring, at what time and where. Manger C's ideas also agreed with Manager A that majority of the data is simple, and the data is structured, which makes the comparison of data *quite easy* with similar datasets. Manager E, too, spoke of comparing data. For them, comparing datasets to historical data is an important part of analysis as it enables them to make evaluations and predictions of what might happen in the future. Structured data also allows companies to skip certain parts of data analysis.

*"The structure of data enables us to go straight to, after harmonization, straight to analysis. For example, we don't need to use neural networks to figure out what the data is saying."* Company A

Harmonizing happens when data is in different formats: some might be an absolute value, some parts of a thousand and some percentages of a maximum. So, they need to be harmonized to be able to compare them, says Manager A.

Manger A also described that there are easy analysis algorithms that try to spot or figure out data points that are exceeding some limits. These deviations are seen as important and usually tricker an alert.

*"We know based on the data how certain things should behave, so that's why the deviations are really the key."* Company C

However, not all deviants are deemed important. Manager C also talked about how outliers, that don't make sense, are cleaned up from the database.

Compared to easy algorithms, Manager A defines that more refined or more complex algorithms require a bit of machine learning behind it to be effective.

*"IoT sensors are following the situation, if everything stays within the control limits, then the algorithm keeps on working as it had been working. Even though we did do the analysis and the changes were made based on that analysis, and still the limits were exceeded then the algorithm changes its function, so that the analysis is better next time."* Company A

Furthermore, sometimes there is no need for any particular data analysis at all.

*"We don't actually to do too much for the data. We just sort of show as it is."* Company C

### 4.2.1 The process of data analysis

Each company has their own process of data analysis. Faroukhi et al. (2020) data value chain (figure 2) described the process in seven links: data generation, data acquisition, data pre-processing, data storage, data analysis, data visualization and data exposition. The process of data analysis, the value creation, combined from all the answers is the following: first the data is collected from an IoT device, and uploaded to a cloud service or a database, which fits to the value creation's process first two links: data generation and acquisition. Then data pre-processing is performed by identifying the data type, the data can be put into chronological order and essentially the data is harmonized or transformed into a correct form. Possible outliers are cleaned, and deviants are found. If needed the system sends out an alarm of deviants that exceed predefined limits. This possibility made by IoT is not compatible with any of the seven links.

Data storage came up in terms of that customers might use different data storage systems that may have to be accommodated in the software-side of the offering. Another interviewee mentioned storing data in passing, overall, there were no extensive findings on data storage.

In the database, data from different sources are combined. Next, Simple calculations are made such as averages and comparisons or other additional calculations are performed. Algorithms such as adaptive algorithms are also used. If needed, mathematicians can also make a new algorithm based on what is needed to know from the data. Moreover, there are analysis such as trend analysis and *Measurement and an exacting data type analysis* (Company A). By comparing to history, predictions of future are made. Together, all these actions form the data analysis part of the value creation process.

The steps are followed by a report that is often automated. The results are preferably presented with graphics and visualizations. Graphics and visualizations can communicate more than a numeric Excel table would, thought Manager E. This goes along with the lines of the original model, where it is said that visualization can reveal hidden patterns and helps to show the insights more comprehensively (Faroukhi et al., 2020). Then, if needed or possible, IoT changes the functionality of the system on site, which is also an opportunity made by a certain type of IoT. This is a new aspect to the data value chain.

As IoT combines data generation and acquisition, it gives the possibility of deviant alarms and changes in the functionality of system. This gives another new adaptation to the value creation model when IoT is used. The adapted value chain has eight links: data generation and acquisition with an IoT device, data pre-processing, alert, data storage, data analysis, data visualization, presenting the insights and report and changes in functionality of the IoT system. See figure 6 below.


Figure 6: Big data value chain with IoT, adapted form Faroukhi et al. (2020)

Not every data analysis needs all of the mentioned steps, some data can be shown as it is, or some IoT may not have all the capabilities and some steps aren't needed in the specific case. This process is also defined by having an IoT solution that can reduce the needed steps to make sense of the data. When combining different companies' analysis processes, it is not clear which step is made in which order. So, the steps and their order may be subjected to change. The following figure 7 visualizes the whole process of data analysis with IoT.

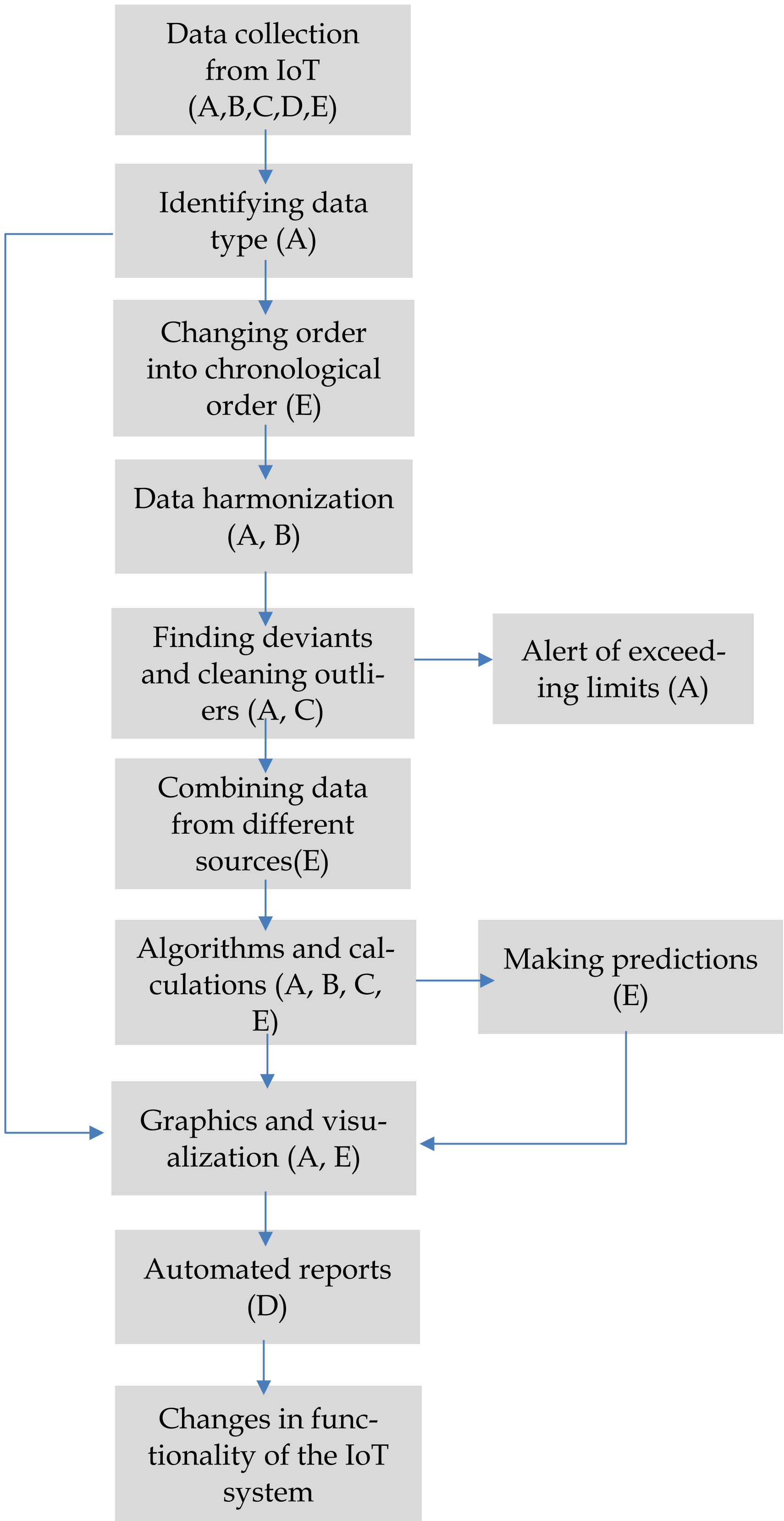


Figure 7: Data analysis process

Similar characteristics or words used about data analysing and value creation between the interviewed companies were automated (B, D, E), simplicity (C, E) and mathematical: such as calculations of averages and parameters (B, C, E), or algorithms (A, B). Senior manager B even called their data analysis *pure mathematics*. Interesting characteristics also mentioned were result-driven, fast and minimalistic, traits indicate that data is analysed only as needed.

*"We ask what they* (the customer*) needs. We figure out what the need is, after which we modify and edit the data so that the need is fulfilled."* Company B, translated

The need steers the analysis, Manager E said that they only do what is needed to bring added value, nothing more. Manager D also mentioned that the data analysis might vary by the customer, however all the customers are looking for a similar thing: one complete view of how things are doing. This opinion is in line with Manager C's ponderings about valuable data giving better understanding of overall state of the business mentioned earlier.

#### 4.2.2 What role does IoT have in the value creation process?

IoT seems to make changes in the value creation and support the data analytics process. However, when directly asked what role does IoT have in the value creation process the main benefit mentioned was that it is the way to collect data. Some even saw that as the only value adding benefit.

*"IoT does nothing on its own, brings no other added value than data collection."* Company E, translated

There was even a question if IoT even enables anything for the value creation.

*"IoT doesn't enable anything for us but we enable IoT… We provide the monitoring device, and we provide the place for the data to be, collected and analysed, and well that allows for data to be used."* Company D

The value added by IoT is not an easy question as it depends on the definition of IoT and how complicated version of it is being used, said manager D. The more complicated version, the more possibilities for added value. Data collection is not the only value of IoT devices when there is a more complex IoT system in use.

*"There's also a two-way function, so it's not just data collection, but many IoT devices can also change the system functionalities… It is a two-way communication, not just data collection."* Company A

IoT also allows a connection from a distance, which can enable a remote access that can make things easier.

*"Without it (*IoT*), then we wouldn't have, I mean, we would need really physically go to the machine to get the information so of course, that is the main benefit… Customers typically, they can have such big like sites and... It takes a lot of time and effort to go and see physically from the machine that what is wrong with them but now they can see the data directly."* Company C

Moreover, to realize the value, there should be multiple IoT devices collecting data.

"O*ne single sensor doesn't actually mean pretty much anything"* Company D

IoT also brings value by doing more accurate and certain work than humans would do, see things that human eyes could not see and see the situation in the same way every time, stated Senior Manger B.

## 4.3 Companies' value capture and business models

Overall, in most cases, the customer is primarily paying for understanding, understanding the machines or the system better, and with that, be able to make better decisions or make needed modifications. What also seems to be in common between the companies is, that getting real time information and speedy reactions is seen to be a reason why customers choose to buy their offering. Real time statistics can for example bring new ways of working for the customer.

*"It's important, that based on the data they can at least try to estimate the behaviour of the machine as well as possible meaning, that they also understand whether it's close to breaking up or whether the machine is working perfectly, meaning that they don't need to pay so much attention to it right now."* Company C

*"They* (customers) *are paying for a big picture. … They see the big picture and then they can proactively plan and, when needed, react as fast as possible."* Company E, translated

Companies C, E and F mention that knowing more and making better and faster decisions lead to financial benefits that motivate the buyer. Company F's solution for example helps to prevent broken tools and be more effective, therefore make savings. With company C the customer for example wants to make sure there is no idle time when the machine is just standing still.

*"I would say their main motivation is to, specially to sort of cut down the unnecessary costs."* Company C

Manager A thought about how data is the middle part, the engine in the middle, for why customers buy the offering. There is a whole value chain that covers more than that, from the identification of the issue to the end solution. In the end the customers buy the offering to solve their problems. Manager D, on the other hand, highlights that the value is in data. The data offers verification of, for example in Company D's case, the surrounding environment. With Company B the customers were seen to be incentivized by the possibilities their offering bring that couldn't be done by old means.

Most of the companies thought that their offering is unique, or at least it is in their own industry. Manager D for example wondered how any single part of the offer isn't unique but as a whole, the way they do things and combine elements is completely unique at this time. Senior Manager B underlined that what they do creates unique opportunities. Only Manager C didn't consider their offer to be that unique, but still different in a good way from the competitors.

*"Our competitors have quite similar products, so I would say, that overall, in our industry, pretty much all our direct competitors have something similar … Not many of our competitors are offering it in this open way that where we are."* Company C

For the companies that don't provide the offer as their main business (A, C, E, F), the motivation for having it was mostly about supporting other sales and being able to serve the customer better as a company.

*"The main motivation is to boost our other offerings, especially selling more equipment and selling overall more services. This is in a way supporting them. I would say that we want to make it as healthy as possible so that it could also be a strong business on its own in the future."* Company C

*"We do this to be more interesting to the customer, to have a more comprehensive supply … This brings added value to the customer."* Company E, translated

*"We offer that for our customers to help to improve the productivity and capabilities, that's clearly number one, but obviously the background for doing this of course, what our motive is, that it is supporting sales, our equipment sales … Maybe we can say that we target that we can help our customers to produce better with our equipment than our competition, and which then would be kind of supporting naturally our own sales."* Company F

Manager A explained that they have four main drives, 1. The megatrend of digitalization, that they want to be a part of, 2. Digital visibility, that they can better communicate with the customer, 3. It gives them functionalities that they couldn't provide by other means, which is also a driver for their traditional business and 4. The megatrend of sustainability, where for example they can monitor and improve energy consumption with this offer.

### 4.3.1 Business models

Half of the companies (A, C, E) mentioned software as a service (SaaS), or a modified version of it, as their business model. Also, Company D identified it as a solution as a service type of business. All of the companies have (in the case of not launched system yet, will most likely have) a yearly or a monthly fee for the service, where there might be an initial fee in the beginning.

"*Product name, *is a SAAS based business that has a consultation part in the start … after that for the foreseeable future the customer pays monthly or yearly fee for using the system and all of its functionalities from that module, or modules, that they have bought."* Company A

*"We are something of a solution as services, since we have the software side, we have the hardware side and we have the actual service, as in customer service*." Company D

With companies A, C, E and F the fee is tied per a certain entity such as a building or a machine.

*"The contracts are machine specific so, … for one equipment per year … let's say if you have like 40 machines, then you basically pay 40 times the license and of course you get some volume discounts."* Company C

*"The customers pay according to how many monitored sights they have connected to this system, so they always pay a small fee per sight per month."* Company E, translated

Some of the companies' offering is somewhat modular and the customer can choose which features they want. Manager A compared it to Microsoft office, where you can for example choose to purchase Excel or Word but not PowerPoint. The more modules, the more expensive the yearly fee.

"*So, these different modules are just different aspects, or different products within the* *product name *platform. You cannot buy… there's no way of buying* *product name *as such as it is."* Company A

With companies C and E, the offer is an additional service to their companies' more main products, even though they can also be bought separately by a non-customer. With Company C, the product can be bought as a module for a machine and with Company E the product can be seen as an additional service for their other automation systems. However, Company D doesn't offer additional services:

*"We see everything that is included in the service package as a part of the subscription so thus, not really anything that could be called extra apart from some really, in deep customizations."* Company D

Manager D also pondered that there will be a change in their business model, as the customers have seen their offer a bit too much as product based and not the service based that they are.

With companies, where the big data offering is not the main business, the target audience seems to be mainly the same as for the whole company. However, the target audience can be more narrowed, for example Company F feels the right target audience at the time is larger companies of the contractors who are buying heavy equipment and Company E focuses on a more specific type of their industrial automation solution buyers.

Companies C and E are mainly selling to existing customers of said companies, but it is not a requirement for to be able to buy the offering and implement it successfully. Company F also sees this as a possibility for them.

*"Majority of our customers are such that have at least some* *Company C's *machine, and we have sold just an individual inside solution and it doesn't matter whether they have* *Company C *or not. … That is sort of the most natural thing to get the customer when they buy a* *Company C *machine. Then, if they get this* *Service C *they can sort of learn to see things through that. So, then it's also easier to expand that when you know do you want to see your other machines too with the same system. "*Company C

*"Well, it is of course easier if we are doing upselling and we already have an existing customer relationship. Of course, it is easier when you have existing contacts, but we are also pursuing to get new customers. … It doesn't necessarily need our products to work."* Company E, translated

Company E also saw selling to brand new customers as a way to start the conversation, and with that, be able sell other products and the offer would be a part of the whole service that their company is providing.

With company D and F, there was mentioned an interesting overlap between customers where both the customer and their subcontractor are interested in the same product because they both want the same information.

*"We are thinking about the logistics, it's the main target audiences. There are people who are actually carrying something, not necessarily companies that are shipping something, but those that are carrying those shipments. But on the other hand, those who ship out products are interested. This might sound a bit absurd but, in some cases, both the shipper and the carrier are interested in the product. So, they might have each their own monitoring device next to each other and both want that information to their own system since there is quite often situations where the companies aren't actually coordinating and stuff like that, too deeply."* Company D

Basically, all the companies in their own way offer a basic solution with an interface, a platform, that they try to keep the same for different customers and customer groups. They try to keep the customizations as standard as possible, by showing different features and functionalities of the same platform or service that acts as a personalization for each individual customer. Company B sees that they have a generic solution and that suits well for different customer groups.

*"No actual coding software development is done for each individual customer. So, it's just some functionalities of the platform that are used to personalize service for each individual customer."* Company A

*"The basic system we have is standard, we have a product, but it may need a little customization based on the need of the customer … but of course we try to make as little changes as possible … We try to bring the data as similar as possible to the interface. "* Company E, translated

However, most of the companies did admit doing some sort of individual personalization if the situation and customer really ask for it.

*"Well, it's standard in a sense, but huge enterprises are used to having a custom solution in any case or in pretty much anything they do, so we are willing to accommodate for that as well. And if a customer orders large enough volume, they can get it a lot cheaper of course."* Company D

*"Like most software service products, the key thing is that you know you get the benefits through scalability … We don't need to do like customer customization too much, basically we don't do it at all. It's very exceptional if we do something specifically for one customer because the point is always trying to make such things that benefit for the whole or maybe pretty much the whole customer community."* Company C

This way of thinking might be the result of using SaaS thinks Manager A as *the power of every SAAS-platform in the universe* is the ability of giving the benefits of development to all or most of the customers depending on their version of the offering. That is why Company A doesn't want to do customer specific changes into the system, they want it to be as versatile as it can be that it can be implemented to different customer groups by changing parameters without additional software development.

Most of the companies (A, B, C and E) said that they don't believe their business model to be unique. This can be explained by the fact that most of them are using SaaS, that is a well-known model.

*"The business model, I would say is quite similar that discover SaaS based yearly licenses, so I would say that is quite normal."* Company C

Company D thought that their solution as a service is somewhat unique as it is not a unique concept but it is *pretty rare*, and Company F thought that although in general the model isn't unique, it is in their industry. However, manager A had an interesting thought about big data business models:

*"I think there are no unique business models with big data. … I think there are differences within the businesses* (that are similar to theirs) *even though the basic model is the same."* Company A

### 4.3.2 Who owns the data?

As with any big data offering's value proposition and business model it is important to understand and define who owns or has rights to the data. Although, who is the owner of the data might not be as simple question as it sounds. Who can truly even own data? Manager C wonder how the ownership of data is debatable at least in the legal perspective when the data is in a customer's machine but on the other hand the value of the data comes from their system. Manager C still believed that in their case the owner is the customer. Companies A and E also stated the owner to be the customer.

*"The owner of data is always the customer. We have the right to use the data, but the owner is always the customer."* Company A

Only company D said that they own the data. Regardless, it seems that the contract and rights for the data stand to be the most important factors in the question of owning the data.

*"With the terms it's made clear for the customer that, you know, we can handle the data in order to make it visible for the customer, but we are not actively taking a stance that who actually owns it because actually the ownership, in most cases, it's not that interesting for the customer … I would say that it's more about the rights, that who can see them in what kind of situations."* Company C

Senior Manager B declared that the ownership depends on the contract and manager A said they have rights for the system, but not for the data. They compared the rights for data with an example of Microsoft Office Word. The writer owns the writing and rights to use Word, but Microsoft owns Word but not what is produced with it.

While the customer would own the data, Company E hopes to be able to utilize the data in general form, not showing individual customer data but utilizing the data as a data bank.

# 5 CONCLUSIONS

In conclusions, the main findings of this study and their relationship to the theory presented are explained, after which managerial contributions are clarified. Lastly this study is evaluated, and further research need is suggested.

## 5.1 Theoretical contributions

This study makes numerous theoretical contributions. This research further demonstrates that there is value in data and the importance of it is only rising with digitalization in the minds of business managers. The added value is also seen to bring monetary benefits.

Added value is actionable and can give predictions of the future, trends and model the surrounding world. IoT gives real time data which allows faster reactions to it. This helps to prevent value loss in data collection and processing latency highlighted by Pigni et al. (2016). According to the findings, data is also valuable when it is all comprehensive. IoT was thought to bring concreteness and make the accuracy better, therefor adding value to the data. This is in line with Attaran's (2017) thoughts of how IoT gives fast data retrieval and is associated with better quality data. Overall, IoT was seen as a way to collect data and as an enabler of remote access.

The interviewees, part from one, saw their offering's value being more than the data value itself. The data is the engine in the middle, as one of the interviewees put it. The offer as a whole is a solution to the customer's problems. The companies also focused on the monetary benefits of their offer when discussing what value it brings.

For companies that don't provide big data with an IoT solution as their main business, the motivation for it was supporting sales and being able to serve the customer better as a company, for example give functionalities that couldn't be offered in any other means. Other driver for providing this kind of offer was staying in the trend of digitalization. This finding goes well with Hanafizadeh & Harati Nik's (2020) outcome that big data gives a new novel source of revenue and gives competitive edge.

### 5.1.1 Value creation

This study discovered that IoT makes data value creation easier. The data gathered form IoT devices is often structured, which makes the data analysis process less complicated. There is no need to identify and organize the data into making sense, so certain parts of the analysis can be skipped, and it makes compering the data simpler. The main characteristics used to describe data analysing and value creation were automated, simple and mathematical.

This study proposes a new adaptation (figure 6) to the Faroukhi et al.'s (2020) data value chain model (figure 2) when IoT is used. The adapted value chain has eight links: data generation and acquisition with an IoT device, data pre-processing, alert, data storage, data analysis, data visualization, presenting the insights and report and changes in functionality of the IoT system.

First the data is collected from an IoT device and uploaded into a database. The data type is identified, it can be transformed into another form and put into a specific order. Essentially the data is harmonized. Then outliers are cleaned, and deviants are found. If needed or possible, the system sends out an alarm of deviants that exceed predefined limits. Harmonizing and cleaning outliers fall to the data pre-processing as it helps with the noisiness of data, therefore the quality of the data is improved, which in turn helps the data analysis (Faroukhi et al., 2020; Rehman et al., 2016).

In the data analysis part of the chain, the data from different sources are combined, simple calculations are made, such as averages. Existing algorithms should be used, or new ones created based on what is needed to know from the data. Other analysis can be performed, too. By comparing new data to history data, predictions of the future can be made.

All these steps are followed by a report that is preferably automated and displayed via a software platform. The results should be presented with graphics and visualizations, that tell more than spreadsheet of datapoints would.

Finally, if needed or possible, changes in the IoT's functionality are made automatically or manually.

### 5.1.2 Value capture

The customers are often existing customers of the company that provides the IoT offering. With companies, where the big data offering is not the main business, the target audience for new customers is mainly the same as for the whole company. However, it can be more narrowed. With some of the companies the offer is an additional service to their main products, even though they can also be bought separately by a noncustomer.

When considering Pravinen et al.'s (2020) business model variation for data monetization (table 2), the studied companies seem to provide either to current customers or to actors in current value chain. Even though the customers don't have to be an existing customer of the company, the data is not really offered openly to anyone, such as investors or authorities. The companies have also passed just selling aggregated data to providing insights and are at least trying to create a scalable service. They have surpassed the first step of data monetization business model that would be selling aggregated data to current customers as an additional feature, but not by much, as it still seems to be the underlining idea behind some of the offers (Parvinen et al., 2020).

The companies identified their offers as services instead of products and focused on service business models. This was important to them, as one of the companies is making changes in their business model in order to be seen more of a service than a product provider. This is a common trend in IT (Reen et al., 2017) and seems to follow two out of three IoT business model patterns by Fleisch et al., (2014): integration of users and customers in their value creation chain, service orientation, and core competence analysis, where customer use data collected and analysed.

The focus of the offer was also more on the digital layers of IoT (service, analytics, connectivity) and the companies seemed to try to integrate the physical layers (sensor, physical thing, connectivity) to the service itself (Fleisch et al., 2015; Wortmann et al., 2020). This doesn't fit with Fleisch et al., (2015) value creation formula well (Thing + IT = thing-based function + IT based service). Instead, the thing + IT value creation seems to be realized but value proposal is focused almost solely on IT based service or at least they are separated, for example if a machine has IoT, the value of the machine is separated from the value that of the machine together with IoT sensors. This could be the result of the interviews being centred around big data and IoT, and their value creation and capture, or a result of having also a separate offer line for the IoT service form the basic services the company offers to their existing customers.

Another interesting finding is that the larger companies where the offer is not the company's main source of revenue, IoT is used to provide new digital functions and services to the existing product. When comparing the companies' offer and business model to the theory background, the business models seem to follow digitally charged product (Fleisch et al., 2015) or the add-on (Suppatvech et al., 2019) models. On the other hand, the smaller companies where this is their main source of revenue focus on selling sensor data or digital services where IoT components are part of the service price. The business models mimic selling sensor as a service (Fleisch et al., 2015) or a digital service (Wortmann et al., 2020) models.

Half of the companies themselves identified to have a software as a service (SaaS), or a modified version of it, as their business model. One company identified their business model to be a solution as a service. Also, the companies have a yearly or a monthly fee, often per a unit. There might be an initial fee in the beginning too.

Based on the studied subjects, companies don't want to make customizations but instead they try to offer a versatile interface that can be used in multiple ways, so the services are at least somewhat modular.

Most of the companies thought their offers to be unique, or at least in their own industry. However, they don't believe that their business model is unique. This could be explained by the fact that most of them are using SaaS, that is a well-known model. One of the interviewees even said there are no unique business models with big data. These findings contradict Wortmann et al.'s (2020) concept that IoT will disrupt existing business models. However, in cases of companies whose offer is not their main business, the model for the IoT service seemed to differ from their more basic models such as providing a product for a price with no running yearly fees. So, inside a company it could be said, that selling big data changes the business model used, that carries on the belief of

Najjar & Kettinger's (2013) that monetizing big data creates a new way of doing business. The result also enforces the indication that if a company wants to be a strategic player in the big data and IoT markets they should rethink their existing business model (Ju et al., 2016).

Overall, the outcomes of this study mostly repeat what studies think data monetizing is: tapping into untapped potential (Pigni et al., 2016), new product development (Johnson et al., 2017), selling data (Najjar & Kettinger, 2013; Wixom & Ross, 2017) and bartering or wrapping data information around an existing product (Wixom & Ross, 2017; Woerner & Wixom, 2015).

## 5.2 Managerial contributions

To get monetary benefits from their data, mangers should consider how they can make their data more actionable and to think of models and algorithms that can do predictive calculations by finding repetitive trends that can lead to predictions of what is coming next. It is good to remember that data insights entail the modelling and interpretation of data, the combination of which gives the data its value (Grover et al., 2018). Also knowing what kind of data is valuable, helps managers as it's the companies' job to explore, interpret and deliver value (O'Cass & Ngo, 2011).

If the rise of data and IoT really are industry specific as the findings suggest, it could be that getting into the action now would still give the company the benefits of being one of the first comers.

Mangers should consider using IoT solution to gather big data as it can be cost effective by reducing the need of manual work and human intervention and error. This would leave more time of the personnel to do expert work instead of repetitive data gathering and analysing tasks.

This study provides relief for managers who are considering using IoT devices to collect data but are worried about the complexity of its data analysis. According to the findings, analysing IoT's data is considered to be easier than any data analysis, in some cases, the data doesn't even need any particular analysis and can be presented as it is. Also, the structuredness of the data makes it easier to provide predictive results of the analysis, as it is easier to compare data from different points of time, that is important value point for the customer. Managers should however keep in mind that IoT's benefits depend on the definition and how complicated version of it is being used, the more complicated the more possibilities for added value.

Moreover, this study provides information of why customers choose to buy an IoT big data offering in the minds the providing companies. They are paying for understanding, which enables better decision making. In addition, the customers are interested in real time information that enables speedy reactions. Better and faster decision making can lead to financial benefits, such as cost savings. So, in the end, customers are interested in monetary benefits that the data can indirectly offer. Data can also give important verifications.

There was an interesting finding about overlapping customers where both a customer and their subcontractor are interested in the same service. This leaves questions: Does this happen often? Is there a need for products that enable scrutinizing of subcontractors? This could be an interesting business opportunity for managers if there is a need for ways to supervise subcontractors. This however should be further studied to find out the possible size of the need.

This research also provides a new IoT generated big data value chain. It is important to learn to work on the data resource as it increases the value and gives new use value to it (Bowman & Ambrosini, 2000; Liang et al., 2018). Data analysis is a way to maximize data's value (Liang et al., 2018). The findings suggest that it should be automatic, simple, and have algorithms and calculations. Data should be analysed only as needed and analysis should follow the needs and wants of the customers.

Companies with a bigger offer base could start by adding IoT to their product and give additional functions, or digital services to the existing offerings. Smaller new companies could sell sensor data or digital services where the hardware doesn't cost extra.

Based on this study's findings, managers should consider a SaaS business model for their new offer, that has a modular software platform and a subscription fee. Customer specific customizations should be avoided, except integrating systems for big clients, instead focus the development to the main platform where it benefits the whole customer base.

Lastly who would be the owner of the data, is a noteworthy question to ask when thinking about selling big data. Yet it is not that simple to answer. It can be debatable from legal perspective, for example the data might come from the customer's machine, but the value is coming from the providers system. However, in most of the studied companies, the owner of the data was the customer. It is essential to have rules of what kind of rights the parties have on the data in the contract and declare ownership.

## 5.3 Evaluation of the study

Like with any research, this study has its own limitations. One of the limitations is related to the study sample of six interviews, in which the findings are based on. The interviews reflect the subjective opinions and views of the interviewees. There is no guarantee if the interviewees have disclosed the truth completely, they might have wanted to keep the company's business model more to themselves in fears of exposure, despite the measures taken to assure anonymity of the interviewees and companies. It is also possible that they have exaggerated some aspects for example of their data analysis capabilities or tried to present themselves and the company in a positive and rational light. In addition, there was only a one representative of each company, which might lead to not being able to wholly comprehend the opinions of the company on their big data value creation and capture.

The researcher theirself is a significant research tool too (Eskola & Suoranta, 1998, p. 151). In qualitative research it is almost impossible to be fully objective and the researcher filters the information through their own subjective lens as they are the creator and interpreter of the study framework (Tuomi & Sarajärvi, 2018, p. 119). That being said, the researcher acknowledges that her prejustices or other subjectivity may have affected the result of this research.

For the researcher, this was the first-time using interviews as a study method for qualitative research and it takes practice to be nondirective. Being nondirective is important as the interviews' idea is to let the interviewees the opportunity to express their own meanings and ways to describe the situation (Yin, 2016 p. 144). For example, the questions should be constructed in a way that the interviewee can't answer yes or no (Vilkka, 2021, p.103). Although this was considered with the structured questions, unstructured questions might not have been constructed in the best possible way.

The researcher did not specify any specific definition of IoT to the interviewees before the interview. Big data and IoT should have been defined beforehand to have a better common understanding of what they mean to the interviewees, who answer based on their own interpretations of the subject.

It is good to note that any theoretical finding should be scrutinized and viewed critically. It is often thought that qualitative research gives deep and profound information, but it is not well generalizable (Alasuutari, 2012, p. 180). The research results represent the situation in a specific context and might not be fully generalizable to other contexts. The results need further studies to hold significance.

This research was done in a manner that follows good scientific practice where the researcher follows ethically sustainable data collection and research methods, such as careful and accurate citation (Vilkka, 2021, pp. 37, 39). The researcher did not receive any funding and the research data was treated confidentially.

## 5.4 Suggestions for further research

Qualitative research is good for preliminary investigation and would benefit from further research with quantitative studies to better generalize the results (Alasuutari, 2012, p. 180). So, further research should examine the topic from a more quantitative point of view to verify if the results repeat themselves. This study has focused on value creation and capture with business-to-business context, more studies in the business-to-consumers could lead to different observations and give valuable insights.

One of the findings of this study indicated that IoT makes the data analysis and its process easier. It would be interesting to investigate if this can be supported by further studies and find out how much less effort is needed compared to other big data analysis done without the help of IoT devices. In addition, does it lead to overall monetary savings is also a great question to ask.

This study highlights the value of trying to predict the future of, for example if a machine will break down or need specific maintenance. It was even referred as the Holy Grail. Especially for managerial perspective it would be beneficial to understand better how valuable it really is to the customer and how companies have accomplished providing this.

One of the major empirical theory contributions of this study is a proposal of an adapted IoT generated big data value chain. This study is not qualified to make such theoretically valid models, so the presented value chain theory should be further studied to see if it holds any theoretical significance.

Finally, the findings suggest that there is a difference in business model preferences between companies where they have added big data and IoT services to their offer base and companies that solely offer big data and IoT services. The research sample is not large enough to make conclusions if this is a trend, so further studies are needed on the subject.

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