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Making Money Selling "Maybe" - The Pricing of Predictions

A literature review of pricing models of goods and services

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Master thesis, Master of Science in Economics and Business Administration, Business Analysis and Performance Management

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

Advances in technology is a game changer for business. Today we can predict faster, cheaper and better than ever before (McKinsey, 2018), which enables humans to work smarter and faster. The technological development changes the way the world works and how businesses create, capture and deliver value.

Apple transformed the music industry when they in 2003 introduced the iTunes Music Store (Apple, 2003), distributing songs separately online and sidelining the traditional CD. Using technology, they found a new way to deliver their product. When Spotify later launched in 2008, also they made individual songs available (Spotify, 2019). Changing the game was the way they charged their customers. Instead of charging for each individual song, Spotify charged a monthly fee in exchange for access to all available music files.

A part of businesses maximizing their benefits from new technological opportunities lies in their pricing scheme. As technology advances and machines can do what humans do, predictions will become both better and cheaper. As a result, the use in businesses will accelerate in the time to come. The main objective of this thesis is to find out how pricing models of goods and services can be used in the pricing of AI-based predictions.

Through a literature review of pricing, we identify pricing models guiding the seller in how to charge the buyer. Going through 1,745 articles we identify three broader categories; unit-based, subscription-based and output-dependent pricing. Reviewing 60 articles in detail we placed subcategories of pricing within these categories, forming a picture of the pricing literature from 2000 until today.

Combining pricing models found in the literature review with characteristics of predictions we create a model for decision making. Dependent on willingness to pay and degree of judgment needed for the given prediction, we suggest a suitable pricing model. With this we aim to help the decision maker make better and more substantiated choices. In the case of low willingness to pay we suggest subscription-based pricing regardless of the degree of judgment needed. As for high willingness to pay we recommend prediction-sellers to use output-dependent pricing in the state of a low degree of judgment needed and unit-based in the state of high.

Acknowledgments

This master thesis is written as a part of our master's degree with a specialization in Business Analysis and Performance Management at the Norwegian School of Economics (NHH). As predictions become both better and cheaper, we believe the use in businesses will accelerate in the time to come. We found it interesting to research what pricing model is suitable for businesses who either work with predictions today or consider changing their business model to include predictions in the future.

Working with the thesis has been challenging, especially considering the extraordinary characteristics of predictions and the technology they build on. However, we found this pioneering work both rewarding and engaging.

We would like to express our gratitude to our supervisor Tor W. Andreassen. His creative input and mindset have broadened our horizons, enabling us to look at things differently. Working with him has helped us learn how to use our theoretical skills on practical problems, seeing opportunities and solutions. Why cut costs when you have endless market potential?

Bergen, May 2019

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1. Introduction

1.1 Background and motivation

We had an “aha” moment reading the book Prediction Machines previously this year. We both have experience using Uber and Lyft. Considering these services, in comparison with taxies, we were convinced that the app was the decisive difference. Giving you real-time information of the driver’s location and automating the payment process the app does separate Uber from taxi. Later we understood that simplifying navigation was the crucial part. As satellites and digital maps on phones enabled everyone to navigate from one address to another, the competitive advantage of taxi drivers diminished. The GPS was crucial for the success of the app. To figure out we got it all wrong and understanding the underlying reason was pretty cool. We hope to leave you feeling the same way by reading this paper.

Today one can see several examples of how technology changes the world. Receiving more than three billion search queries every day, Google is able to predict the spread of winter flu in the US down to specific regions and states (Mayer-Schönberger, 2013, p. 2). By the time the next pandemic comes around one will be able to predict and prevent its spread. You might still believe humans are a better judge of character than machines. Studies comparing human recruiters to AI-powered recruiters find that recruits selected by AI on average outperformed those selected by human recruiters (McKinsey, 2018). That is in a profession where human abilities might be considered the most important trait. Even your car can handle itself better without your help. With the use of Autopilot AI, a Tesla Motors Club member claims to have been saved by his Tesla when it predicted a potential car crash and prevented it (Agrawal, Gans, & Goldfarb, 2018, pp. 111-112). Are machines outperforming humans? If so, what does this mean for your business?

Amazon is developing an algorithm enabling delivery of products to customers before they place an order. Imagine getting toilet paper delivered on your doorstep at the exact time you run out, but without having to order it. If Amazon is able to improve the accuracy of their predictions to a level where this anticipatory shipping is feasible, their business model will change dramatically. The past has shown that changes in technology might demand changes in pricing structures. To go from physically owning a CD, to stream all the music in the world on Spotify, entailed going from paying per album to subscribing to access. With today’s advances in technology, the question becomes whether existing pricing models apply or if new ones are demanded. How will Amazon charge for the toilet paper? And more importantly, how will you make money selling “maybe”?

1.2 Research question

The purpose of this paper is to study AI-based predictions, and how pricing models of goods and services can be used in this matter. The master thesis will explore possible pricing of predictions by outlining already existing pricing models. We aim to give insight on what managers selling predictions must consider when making pricing decisions. This includes how the pricing is arranged, not the level of price. We consider the predictions to be sold as an estimated guess, without the associated judgment needed to make decisions. Our problem definition is:

How can pricing models of goods and services be used for the pricing of AI-based predictions?

1.3 Outline

Chapter 1 contains a presentation of the thesis. Pricing is introduced in **chapter 2**. We first present and justify our methodological approach, the literature review. The procedure of the literature search is outlined. The result is a thorough review of pricing literature from 2000 to 2019, where three main pricing models are identified.

Chapter 3 outlines predictions. First, we give an overview of the Internet of Things, Big Data, Artificial Intelligence, and Machine Learning, to create insight to better understand predictions. We present and explain the process from data to decision, emphasizing the complexity of predictions. We highlight judgment and evaluation of predictions, as we find them important regarding the pricing issue.

Chapter 4 includes a thorough analysis of how pricing models of goods and services can be used for the pricing of AI-based predictions. Each identified pricing model, with its associated features, is seen in the context of predictions. From this analysis, we create a prediction pricing model, where the choice amongst identified pricing models depends on the value of the prediction and the judgment needed to be added.

In **Chapter 5** the managerial implications are provided, which includes the thesis' main findings and the answer to the problem definition.

2. Pricing

Kuyumcu (2007) claims that the most important business process is deciding how to make pricing decisions. Businesses exist to create value, and as pricing defines the value of your product or service, the decision regarding pricing is crucial for every business.

If the pricing is done correctly it can contribute to driving profitable growth, while done recklessly it can have fatal consequences. Raju and Zhang (2010) states that pricing strategies can have huge impact on profits, citing a study by McKinsey highlighting how decisions impact the bottom line: reducing fixed costs by 1% will improve profitability by 2.3%; increasing volume by 1% will increase profitability by 3.3%; reducing variable costs by 1% will improve profits by 7.8%; while an increase in price by 1% can prompt an 11% rise in profitability. Illustrating how pricing affects profits, clarifies the importance of setting the correct price and choosing the right pricing model.

The concept of pricing has existed as long as people have exchanged goods and services. A great amount of research is done on the topic, resulting in a considerable amount of published literature. We have reviewed this literature from 2000 to 2019. In the following we explain how we executed this, and present our findings.

2.1 Methodology

This chapter comprehend our methodological choices. To begin with, we justify our chosen research method. Further, we explain in detail how we conducted the literature search, selection, and review. All decisions made and explained in this chapter are taken with the purpose to answer our research question. Limitations and weaknesses of the choices are included.

2.1.1 **Research Method**

The research method includes the approach to the analysis and the collecting of data. Starting out, we conducted informal meetings and interviews with managers who in the future might heavily depend on predictions. This with the aim of detecting the best possible way to answer our research question. We understood that our selected topic was in need of research and that a comprehensive picture of the pricing of predictions might be challenging to extract from interviews.

The literature review represents a method in the field of research as one identifies, record, understand and transmit information relevant to the topic of interest by applying certain strategies and procedures (Onwuegbuzie & Frels, 2016, p. 49). Identifying, recording and understanding pricing literature would be of great help answering our research question. The data in a literature review is the literature collected. There is a great amount of pricing literature, and to conduct a literature review seems reasonable. This would allow us to detect the diversity of knowledge of pricing in the last years (Tranfield, Denyer, & Smart, 2003). Our literature search will not detect the current state of pricing of predictions but map and assess the existing intellectual territory.

2.1.2 **Approach**

We will describe how we conducted the literature review, dividing the process into three categories; search, selection and review. We aim to describe our review process in sufficient detail to improve transparency and ensure replication (Tranfield et al., 2003).

Search

We discussed our topic and research question with the research librarian and decided to use the EBSCO Business Source Complete (hereafter BSC) database for our initial literature review. We are aware of the importance of using a range of databases to ensure wide coverage of available literature (Saunders, 2009, p. 82). Using one database alone for our initial search limits this literature review and is to be considered a weakness. However, in order to make the task feasible in a practical way we found this limitation necessary. The database was chosen due to its features and contents. Some additional databases were applied in the process of investigating the sources used in the literature and quality assurance of the literature. This includes ABI/INFORM Global, Emerald Insight, Science Direct, Scopus and certain books.

The use of BSC enables searching for specific words in different parts of the articles. We specified our search to include articles including "pricing" in either title or abstract. The literature stresses that relevant literature might be excluded while using abstracts as a substitute for the full article, since they only contain a summary (Saunders, 2009, p. 81). We recognize the risk of excluding relevant articles but choose to limit our search this way due to the number of articles on the subject.

When testing different keywords in combination with pricing, we found it difficult to find articles containing models for how to price rather than determining the price level. In the absence of suitable keywords, the thesaurus term options provided by the database were applied. Initially, 24 terms were chosen to avoid missing out on potentially relevant articles. Chosen terms are to be found in the appendix. Using the search specifications, we further limited our search to academic and scholarly peer-reviewed journals, published between 2000 and 2019 in English. The search resulted in a total of 3,216 articles.

Selection

As our initial search resulted in a great number of articles the first part of our selection process consisted of interpreting the relevant thesaurus terms. Reading titles and abstracts we recorded which terms gave relevant hits and which did not. As an example, the term “markets” generated technical articles related to finance and economics. This term, in addition to others, were dropped resulting in a final hit of 1,745 articles.

The second part of the selection process entailed reading abstracts of the 1,745 articles found in the final search. The articles were organized by relevance for our research question, divided into three groups; relevant, uncertain relevance or irrelevant. In this process, the articles discussing how to price products and services were chosen, while those discussing price levels and changes were excluded. The latter was not considered to serve to answer the purpose of our study. This involves excluding methods like cost-based pricing, demand-based pricing, competition-based pricing and dynamic pricing, that all determine the price level. The selection process resulted in 60 articles categorized either relevant or of uncertain relevance.

Review

Finally, we reviewed the 60 selected articles. This process consisted of a thorough read-through, marking of relevant information and categorizing. Rather than categorizing by discipline, research method or chronologically, we present our findings along the lines of three different pricing models; unit-based pricing, subscription-based pricing, and output-dependent pricing. From our literature search, we identified these as broad categories that we considered applicable in the pricing of predictions. This categorization of pricing is also supported in the literature (Shen, 2002). The final review resulted in 23 articles considered relevant for our research question, which thoughts and findings are to be presented in the following.

2.2 Literature review

The literature has shown a growing interest in pricing (Sotgiu & Ancarani, 2004). From ancient times barter has existed, with Mesopotamia relying on trade to get raw materials (Potts, 1993). Trade in goods implicitly gives a unit price. As the world has evolved the pricing has too. We have seen computing and innovative services enabling one to track the usage, resulting in usage-based prices (Balasubramanian, Bhattacharya, & Krishnan, 2015). Some predict that subscription is the future. With technology, digital customers will favor access over ownership (Broughton, 2018). One has seen how Spotify outperformed the CDs. Technology also enables one to measure a broader range of output in an effortless way, laying the foundation for output-based pricing (Iansiti & Lakhani, 2014). In the following, we will provide an overview of the pricing literature in the period between 2000 and 2019.

2.2.1 **Unit-based pricing**

Initially in the presenting of our findings we introduce unit-based pricing. Of the identified models, this might be considered the traditional pricing model. We find a considerable amount of literature, both older and newer, but under several different terms. We emphasize the frequently mentioned model usage-based pricing as a type of unit-based pricing. Some of the terms have multiple approaches and we will present a selection of these.

Measure-based and usage-based

Kwortnik, Creyer, and Ross (2006) define two types of unit pricing: measure-based and usage based. Measure-based unit prices are expressed in dollars per unit of measure, while usage-based unit prices are expressed in terms of dollars per use. To price laundry detergent with dollars per kilo is measure-based pricing, while pricing it by number of wash loads is usage-based.

Confronted with a choice between a 104-ounce package of regular laundry detergent for $4.49 and a 92-ounce premium detergent for $9.39 the customer might be unsure what is of the greatest value. Using a measure-based unit price the regular is priced $0.70 per pound, while the premium is priced $1.63 per pound, favoring the regular detergent. Using usage-based unit pricing, the regular one cleans 13 loads, while the premium one cleans 42, favoring the premium detergent. Calculating we find that the traditional detergent costs $0.35 per load, while the premium detergent only costs $0.22. Kwortnik et al. (2006) find that the right information to make an accurate evaluation of a brands true value is not always provided by measure-based unit pricing.

Usage-based

Bonnemeier, Burianek, and Reichwald (2010) place usage-based pricing in the category of input-based pricing, presented by Hünerberg and Hüttmann (2003) relating to the intensity of use. According to them, usage-based pricing involves paying a pre-negotiated fee to a solution provider dependent on the utilization of the solution, within a given period of time. Examples of pricing parameters used are time or intensity of use of machines, web servers or systems.

The growth of cloud storage, service delivery, and computing are considered the cause of the acceleration of pay-per-use pricing (Balasubramanian et al., 2015), enabling the tracking of usage. In the approach of unit pricing of access services by Essegaier, Gupta, and Zhang (2002) the firms' value of light users or heavy users are emphasized. They suggest that if light users are more valuable, the firm will not charge a usage price alone, whilst they might do so if heavy users are more valuable. These findings are in compliance with light users preferring pay-per-use (Altmann & Chu, 2001). The revenues of pay-per-use pricing depend on the frequency of use (Balasubramanian et al., 2015), which we clarify with an example. For a gym with a majority of light users, people only exercise once in a while. They will not profit from charging per visit at the gym. However, with a majority of heavy users, people exercise frequently and paying per visit will be profitable.

To administer a usage-based pricing schedule one must monitor and record details of usage for individual customers, and the related administration cost can be expensive (Sundararajan, 2004). Moreover, these costs are unrelated to the delivery or production of the good. It is a consequence of a pricing scheme that is usage-based. The ticking meter effect, explained by Balasubramanian et al. (2015), is a psychological cost associated with pay-per-use. This is based on the mental accounting of repeated payments when consumption is coupled to payments (Prelec & Loewenstein, 1998).

2.2.2 **Subscription-based pricing**

Further, the second model we have identified is subscription-based pricing. Pricing with a subscription-based structure is what we define as flat-fee pricing. It gives the customer unlimited access for a specific time period (Mason, 2000). The literature also present a structure allowing unlimited consumption during a specific time period, by the name buffet pricing (Nahata, Ostaszewski, & Sahoo, 1999). According to Sundararajan (2004), there are numerous examples of fixed-fee pricing of information goods where the price is independent of usage. The literature also considers subscription in combination with usage-based pricing. In addition to the flat-fee we will present two variants of this; two-part tariff and bucket pricing.

Flat-fee

Flat-fee pricing charges the customers a predetermined fee. In exchange for the fee the buyer gets unlimited access for a specific period of time (Mason, 2000). As illustrated in *Figure 1* all costs are known at the time of purchase, and independent of consumption.

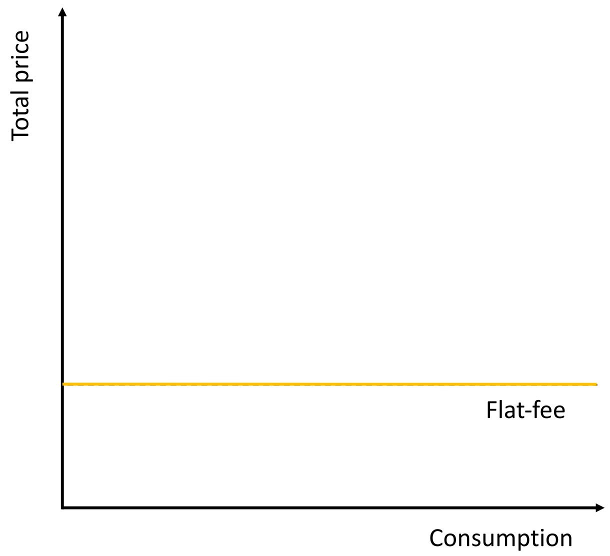

Figure 1 - Flat-fee pricing

Offering customers unlimited consumption with a flat-fee structure is gaining customer preference, even though customers tend to pay more with this structure compared to a usage-based structure, Hinterhuber and Liozu (2014) state referring to academic research. Customers might pay extra if the usage does not affect the price. To illustrate, France's state-owned railway company SNCF created an "all you can travel" for 79 euros a month for 16 to 27-year-olds. This offset the migration of young train travelers. SNCF had 75 000 extra young train travelers, and within months the company reached its annual growth targets (Broughton, 2018).

Train (1991, p. 211) argues that consumers, for the same expected payment, prefer flat-fee over unit pricing and terms this the "flat-rate bias". This bias can be explained by the above-mentioned ticking meter effect (Balasubramanian et al., 2015) and consumers valuing knowing the size of the bill ahead of time (Iyengar, Jedidi, Essegaier, & Danaher, 2011). Balasubramanian et al. (2015) demonstrate that a monopolist should use usage-based pricing if the psychological cost associated with buying is low, and a flat-fee if the cost of buying is high. As for SNCF, the psychological cost of buying for young travelers seemed high.

Essegaier et al. (2002) discuss flat fee pricing of access services, to pay for accessing a firm's facilities but not acquire any right to the facility itself. Bloomberg sells access to information and Telenor sells internet access. The services contain capacity constraints, and firms can only allow a limited number of consumers to access the service at the same time. The users have different usage rates: heavy or light users. Essegaier et al. (2002) find that a flat-fee may be used both when light and heavy users are the most valuable. Valuable is in terms of their willingness to pay on a per unit of capacity constraint. The cost per use will vary from consumer to consumer with a flat-fee (Nahata et al., 1999). Flat-fee pricing subsidizes heavy users at the expense of the light user, and one might risk losing the light users to one's rivals (Essegaier et al., 2002).

Two-part tariff

A combination of fixed-fee and usage-based pricing is common for information goods (Sundararajan, 2004). Essegaier et al. (2002) describe two-part tariff pricing as a combination of per-unit and flat-fee pricing. In addition to the flat fee, the total price increase for each unit, as illustrated in *Figure 2*. Services also offer two-part tariffs. The Santa Monica based airline Surf Air now offers a two-part tariff for its customers (Broughton, 2018). With an annual fee of $2,500, you can fly as much as you want for an additional $500 per flight.

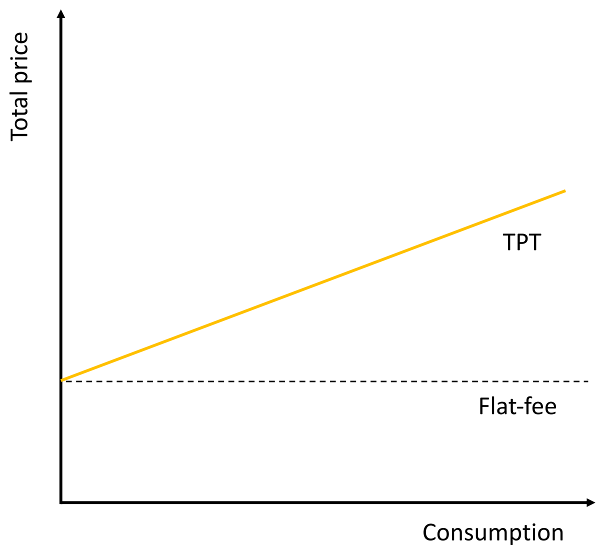

Figure 2 - Two-part tariff

The literature states that this pricing structure can make one vulnerable to lose both heavy and light users to rivals for access services (Essegaier et al., 2002). Frequent flyers might prefer a flat fee over Surf Air's two-part tariff, and the membership fee might make customers who travel less often choose other alternatives. According to research by Iyengar et al. (2011) consumers derive lower utility with a two-part tariff pricing of service, compared to a pay-per-use which gives a higher customer churn and lower usage of the service.

According to Oi (1971), a two-part tariff allows firms to generate higher profits than pay-per-use, given the assumption of the same demand curve. For the same unit price and quantity of sale, an additional income through a membership fee with the two-part tariff will give higher profit. After Prelec and Loewenstein (1998) the price format can influence consumers perception of value and their consumption. This breaks the assumption of the same demand curve (Iyengar et al., 2011). To exemplify, we go from a pay-per-use to a two-part tariff and charge a membership fee, while keeping the price per unit the same. We then assume that customers will experience buying two units as more expensive. This can lead to customer churn, and a total reduction in quantity sold.

The seller can choose to offer different alternatives of two-part tariffs (Schlereth & Skiera, 2012). Considering the example of Surf Air, they could choose to present several alternative pricing plans. In addition to the alternative of annual fee of $2,500 and additionally $500 per flight, they could offer an option with a higher fee and a corresponding lower unit-based price. TPT^1 in *Figure 3* could represent the already existing alternative. As an example, TPT^2 could consist of an annual fee of $4,000 and an additional fee of $50 per flight.

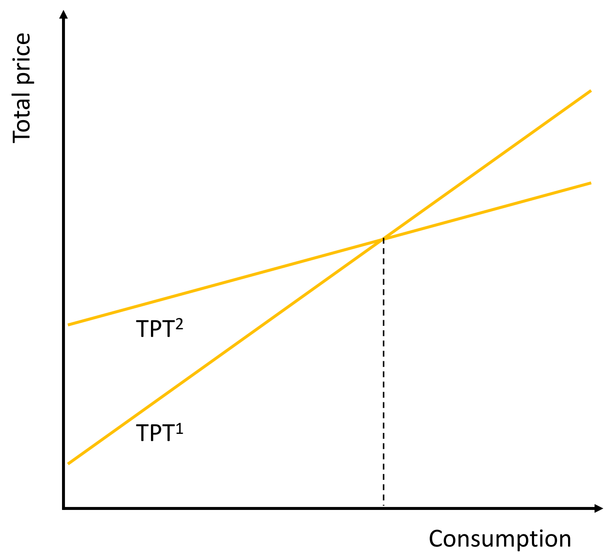

Figure 3 – Alternatives of two-part tariffs

Bucket pricing

A subscription that allows consumers to use the service up to a set allowance and charging a periodic fixed price is by Schlereth and Skiera (2012) termed bucket pricing. Iyengar, Jedidi, and Kohli (2008) exemplifies with car rentals, prescription drug plans, and memberships to health clubs. They charge a fixed fee and allow free use up to a certain level, beyond which consumers must pay a usage-based unit rate. We illustrate this pricing model in *Figure 4*. This type of subscription separates consumption from payment (Schlereth & Skiera, 2012), which enables consumers to enjoy consumption more (Prelec & Loewenstein, 1998). This pricing model does not contain a marginal price and encourages consumers to use a pre-set number of units, unlike pay-per-use and two-part pricing, and hence it is less flexible (Schlereth & Skiera, 2012).

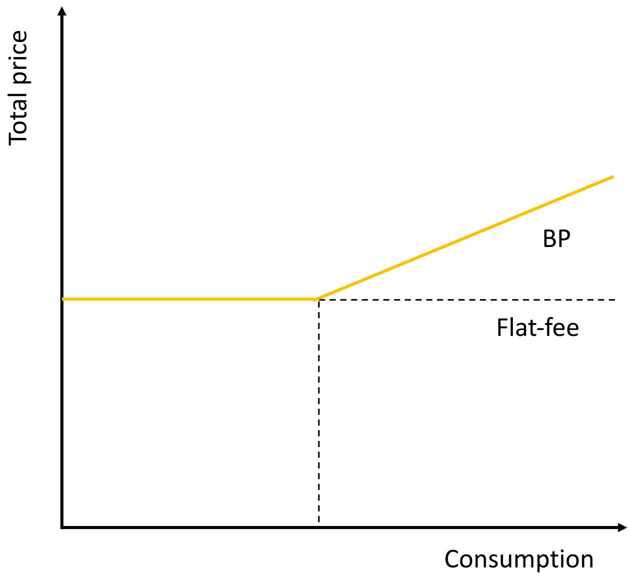

Figure 4 - Bucket pricing

One can also present different alternatives of buckets to the buyer (Schlereth & Skiera, 2012). To exemplify we use Telenor, a provider of goods and services in telecom. In their cell phone plans the amount of data included each month is what determines the price (Telenor, 2019). Using *Figure 5* to illustrate BP[1] is Telenor's option with the lowest amount of data included.

For the price of $25 one gets 1GB of data. BP^2 includes 3GB for $35 and BP^3 6GB for $45. The figure is simplified in order to better illustrate the alternatives, but as shown in *Figure 4* there is a usage-based unit rate for any use exceeding the amount included in the bucket. In the case of Telenor, the customer can choose to either upgrade to another plan or to use data exceeding the bucket with an additional cost for each MB used.

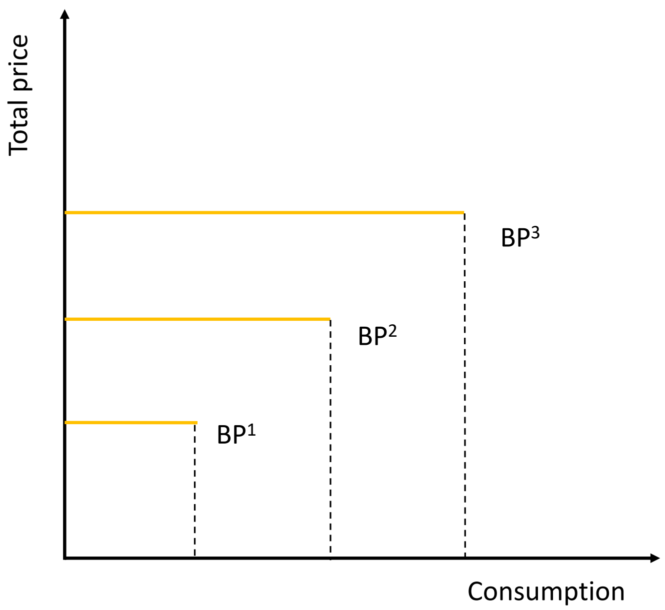

Figure 5 – Alternatives of buckets

2.2.3 **Output-dependent pricing**

In modern times the concept of pricing based on the output generated, has received increased attention. While the traditional approaches in a great manner focused on costs, innovative revenue models are more oriented towards customer value when setting prices (Bonnemeier et al., 2010). As technology keeps advancing, the pricing models does as well. For years we have seen real estate agents being paid a percentage of the selling price. In recent years digitalization has expanded the possibilities of measurement, enabling a greater application of output-dependent pricing. To illustrate, applying IoT General Electric (GE) tie the revenue to performance measures like downtime and miles flown instead of the sale of the engine (Iansiti & Lakhani, 2014).

Nagle and Hogan (2006, p. 18) argue that the pricing challenge is to understand what creates meaningful value for customers in order to set prices reflecting the actual value received. Consequently, innovative pricing approaches focus on the actual output perceived by the customer (Vargo & Lusch, 2004). As identified by Bonnemeier et al. (2010) this causes a change of the measurable performance parameters and switches the allocation base for price setting from the supplier's costs to the value actually realized by the client. Using cost-plus pricing as an example, one priced on the basis of the cost of producing a product in addition to a margin. This pricing does not consider what the customers are willing to pay. Consequently, the price runs the risk of being too high and prevent sales. Using output-dependent pricing, one is ensured to set an acceptable price, as the price is a result of the perceived value.

The literature identifies and presents different concepts considered to be output-dependent pricing. Bonnemeier et al. (2010) distinguish between performance-based and value-based pricing, while Bhargava and Sundaresan (2003) present quality-contingent pricing.

Performance-based

Performance-based pricing involves the seller being paid dependent on the performance outcome, determined together with the customer (Hinterhuber & Liozu, 2014). By this, the performance risk is shifted from the buyer to the seller, and a certain level of performance is guaranteed by the solution provider (Nagle & Hogan, 2006, p. 57). A poor performance from the supplier can result in penalties and reduced prices, but if the delivered solution is according to what was promised, the full pre-negotiated price will be paid (Turner & Simister, 2001).

Before the implementation of the product or service sold, one agrees on a task with a corresponding price. To exemplify, one promises an increase in sales by 20% in exchange of $20,000. The final price is not determined until after implementation. Dependent on the realized change in sales, the price varies as exemplified in *Figure 6*.

Figure 6 - Example of performance-based pricing

According to Nagle and Hogan (2006, p. 57), an ideal price metric would tie what the customer pays directly to both the economic value received and the incremental cost to serve. Performance-based pricing metric is set up to do this. Sharing of risk also makes the product more affordable for the buyer (Piercy, Cravens, & Lane, 2010). As the buyer will get compensation in the event of poor performance, one might be able to buy products and services one would not buy if compensation was not promised. Hinterhuber and Liozu (2014) claim that this pricing is widespread in advertising, complex engineering projects, and industrial services. Further, they expect to see increased usage of this pricing model, but emphasize the large cost associated with it due to the large need for monitoring.

Pricing based on performance requires information and trust, as one depends on the buyer reporting information accurately (Nagle & Hogan, 2006, p. 57). Due to this, performance-based pricing might experience measurement problems (Shen, 2002). Another challenge presented by Nagle and Hogan (2006, p. 57), is the uncertainty held by the buyer regarding the cost of purchase which will not be known until after use.

Value-based

In value-based pricing, the solution provider focuses on the customer's internal processes by delivering optimization or productivity (Bonnemeier et al., 2010). Pricing is thus based on values such as the amount of cost savings generated by implementing the proposed solution (Sawhney, 2004). This results in the supplier directly benefitting from the value added by the solution generated for the client (Hinterhuber, 2004). To clarify, we present an example considering a consultancy firm. If the consultants are hired to increase sales, a value-based price might be 5 percent of profits from increased sales. If the company manages to increase sales, this will also benefit the consultancy firm as illustrated in the example below.

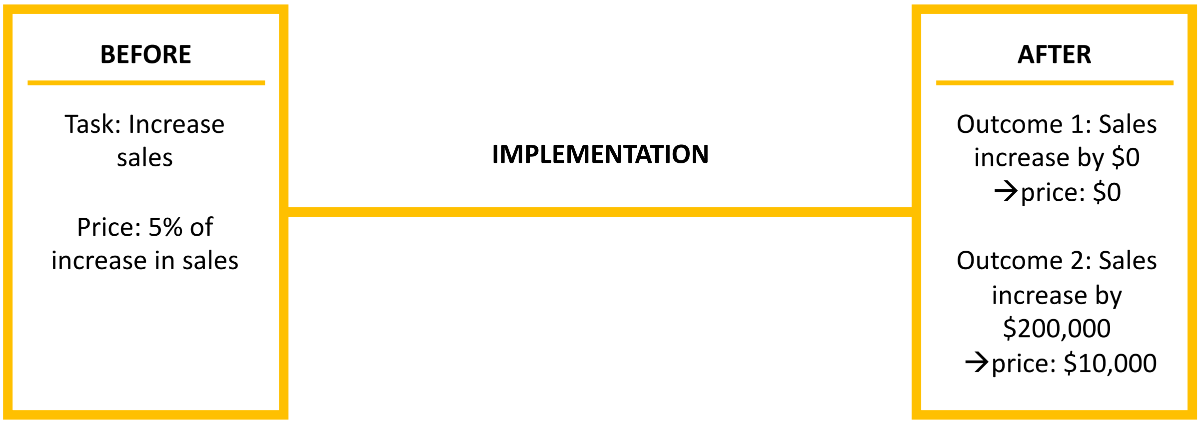

Figure 7 - Example of value-based pricing

Ingenbleek (2007) uses the term value-informed pricing and find that as pricing pressure increases, managerial attention for value-based pricing is in the rise. He defines value-informed pricing as the extent to which a firm takes information into account in the process of determining the price. This information includes perceived relative advantages offered, and how customers trade off these advantages against the not yet determined price.

Measuring and understanding customer value perceptions can, according to Ingenbleek (2007), result in both higher profit margins and higher sales. Firms can avoid charging lower prices than necessary and market a coherent offering where perceived price matches perceived benefits. Grewal, Monroe, and Krishnan (1998) find that when the price payed by the customer is perceived to match the obtained benefits, this can increase the purchase intentions.

The literature also presents difficulties associated with value as a pricing metric. Barriers to adopt value-based pricing include the challenge of objectively measuring value created and resistance from customers to accept unfamiliar pricing approaches (Sawhney, 2004). Further, Ingenbleek (2007) points out difficulties related to evaluating value under conditions of high demand uncertainty. In addition, having information is not enough, as it needs to be transmitted, interpreted and exploited.

Quality-contingent

Quality-contingent pricing involves setting a pre-announced rebate for poor performance, by announcing quality price pairs for various levels of quality (Bhargava & Sundaresan, 2003). To clarify how this can be done, we illustrate by the example in *Figure 8*. Each quality level, here percentage of increase in sales, has an associated predetermined price.

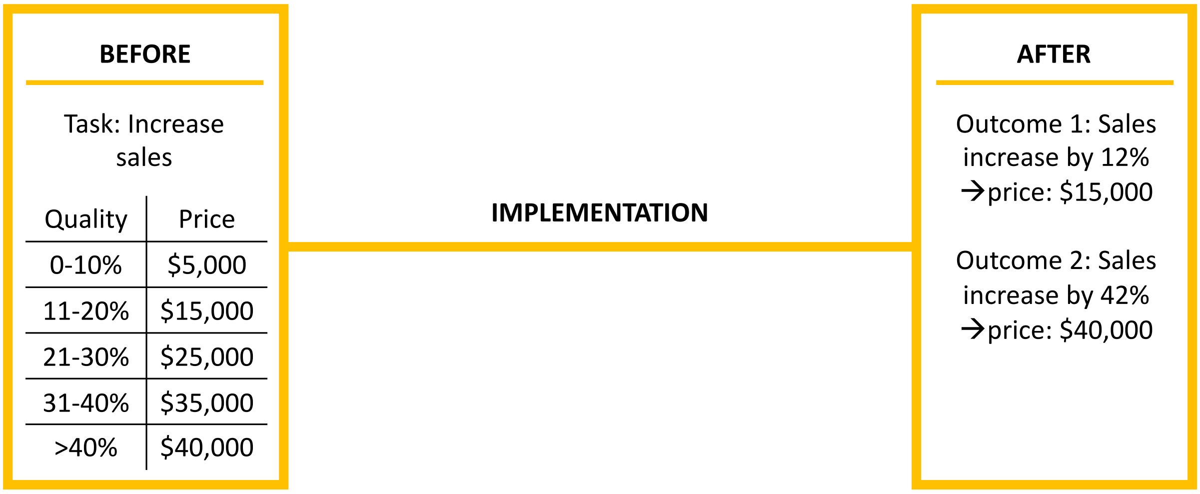

Figure 8 - Example of quality-contingent pricing

Biyalogorsky and Gerstner (2004) relate their study to literature on contingent contracts. They claim that these contracts rely on the fact that the buyer often purchases, either products or services, before the anticipated consumption. With the use of contingent contracts, outcomes contingent on a realized future can be specified. This way one can avoid missing out on a potential deal because of disagreement as to the likelihood of future events.

It would be useful to implement quality-contingent pricing when the market underestimates the firm's performance. In that case, to offer a full-price rebate for misperformance with a corresponding higher price to meet the performance standard, will pay off (Bhargava & Sundaresan, 2003). Bazerman and Gillespie (1999) note that there is a lack of managerial understanding regarding how to design and use optimal quality-contingent pricing, but they emphasize the potential value of contingency pricing under quality uncertainty. Building on this, Bhargava and Sundaresan (2003) say that this type of pricing works well when quality is objectively verifiable and unaffected by use.

Further, Bhargava and Sundaresan (2003) expect performance uncertainty to be an increasingly important issue. They find that contingency pricing is relevant, applicable and implementable in many IT-intensive business contexts to mitigate quality uncertainty effects. This applies to IT products and services, especially as many of these are characterized by quality uncertainty. They also find the pricing metric especially well-suited for IT services because the information structure enables easy quantification, capture, verification, and dissemination of quality and performance information.

2.3 Conclusion

The literature shows a development in the pricing theory. *Figure 9* presents the different pricing models found in the literature review.

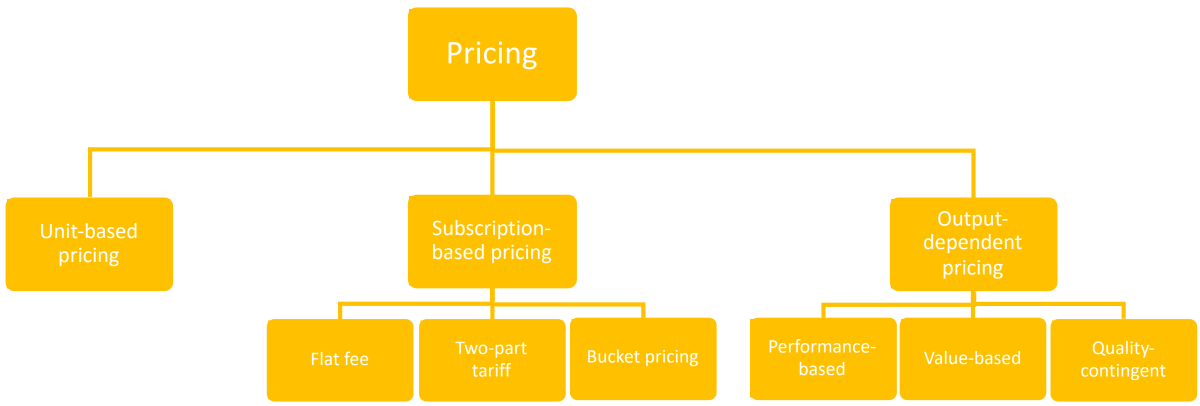

Figure 9 – Presented pricing models

Starting out with the traditional unit-based price we paid a given price for a given product or service. Paying $4.29 for a gallon of milk is an example. In later years, as technology advances, businesses find new ways to deliver their products. Instead of mailing you the physical rental DVD, Netflix manages to distribute its full range of movies online. We now see subscription-based pricing, giving you access in exchange for a fixed fee. For the price of $9 a month, you get access to all movies and series on Netflix. As technology keeps advancing, the pricing also does. With the possibility of measuring we could only dream of some years back, we see output-dependent pricing gaining popularity. Paying for the value received facilitates the selling of products and services where value is not known beforehand, sharing the risk between buyer and seller. Digitalization has enabled GE to apply outcome-based pricing and their revenue is now tied to downtime and miles flown instead of the sale of the engine.

Each day new possibilities arise. Will these pricing models continue to be used or will there be a need for new ones? In the pricing of predictions, will one of these pricing models suffice? To answer this question, we need to understand what predictions are.

3. Predictions

Predictions already surround us in our everyday lives. Considering a regular afternoon, you might read an online newspaper. Using data of what you have read in the past, the newspapers predict what you are likely to have an interest in reading and present you this content. You may want to check your mail, where Gmail has already predicted which emails are spam and which are not. If you then choose to watch a movie on Netflix, they predict what you would like to watch next and present it to you. Not only do they present suggestions, but the movie you are watching might also be the result of predictions based on gathered data. If you choose to finish your day shopping online, Amazon predicts which products you may want to buy.

In order to determine how to price predictions, we need to understand what they are. As a step towards this, we start by providing an overview, placing predictions in the context of the Internet of Things (hereafter IoT), Big Data, Artificial Intelligence (hereafter AI) and Machine Learning (hereafter ML).

3.1 The IoT, Big Data, AI and ML

The **IoT** is a network of interconnected devices, systems, and services (De Cremer, Nguyen, & Simkin, 2017). This could for instance be your Apple watch. Your watch is connected to the internet, and when someone calls on your iPhone you answer from your watch. Your phone and your watch are in a network of connected devices. Within the network, computers can observe, identify and understand the world (Ashton, 2009). As for the Apple Watch, it can sense a fragment of the world: your heart rate, your location through the day and the number of steps taken. From this real-time data, the device gives you a friendly reminder when it is time to exercise. This underlines the importance of updated data. IoT devices obtain data aiming at an automated data extraction without being limited by human-provided data (Elazhary, 2019). When Apple extracts your heart rate data, it does not rely on you providing it yourself, but simply to wear your watch. One avoids the biases associated with data collected through sampling and questionnaires as the data is collected passively.

IoT devices make data gathering easy and effortless (De Cremer et al., 2017). A larger amount of people are willing to monitor everything and everywhere to achieve improvement (Tarabasz, 2016). The smart toothbrush by Kolibree lets you monitor dental habits. By allowing monitoring of kids using it, parents aim to better follow up toothbrushing habits. At the same time, the cost of data acquisition has decreased, while storage and processing power has increased, resulting in more stored data (Zaslavsky, Perera, & Georgakopoulos, 2013). As more people are willing to accept products with sensors, and the ability to store the data is better than ever, the IoT and its devices generate large volumes of data (O' Leary, 2013).

IoT is one of several inputs that generates **Big data**. Originally Big data referred to data sets bigger than the norm (O' Leary, 2013). Since then, the term has evolved to describe the expanding amount of digital information generated from transactions, social media, enterprise content, mobile devices and sensor data (IBM, n.d.). The data aggregated from IoT-sensors, like the data from an Apple Watch, is therefore one of several inputs in Big data. Mayer-Schönberger (2013, p. 28) claims that the size of the dataset, the absolute number of data points, is not what makes big data. What classifies data as big is that as much of the dataset as feasible is used, instead of using the shortcut of a random sample. Big data thereby involves the efforts to make the information analyzable (O' Leary, 2013). This includes, amongst other, to integrate different types of data. As an example, scientists have accurately predicted dengue fever outbreaks weeks in advances applying Big data (HUB, 2013). Making meteorological, socio-political and clinical data analyzable, they found patterns for dengue fever.

To address the feasibility of the data, IBM's four V's are appropriate to consider. First the volume of data, how much data do you have. Second, the velocity of data determining the grade of real-time data. Third, the variety of data. Different forms of data must be accounted for. Fourth and final, the veracity of the data. Is the data trustworthy? Advances in technology allow us to efficiently process this massive amount of data and extract value from it (Zaslavsky et al., 2013).

AI is one way to extract value from data. AI can be defined as the study of how to make computers do things which at the moment, people do better (Rich, Knight, & Nair, 2009). Human intelligence can be simulated in different ways. One way is by feeding the machine if-then statements working as rules, telling the machine what to do in different situations. Considering a translator program, one would feed it words in different languages. If asked to translate a sentence from English to Norwegian, it would look up each word and present a sentence, directly translating each word. We taught it to switch out "Hello" with "Hei". Another way to simulate human intelligence is by training algorithms to classify information by itself.

Continuing with the translator example it would be fed sentences humans have translated. By making a pattern from these and learning it might be able to translate the sentences with the correct syntax and meaning, if it is to achieve a certain level of accuracy. AI contains different techniques and covers identifying underlying rules and patterns, a system's ability to perceive data and to move, control or manipulate objects (Kaplan & Haenlein, 2019).

The last example is an example of **ML**, which is an application of AI (Bellam, 2018). While AI in a broader context includes how machines learn to do what humans do, ML can be thought of as a subcategory of AI. ML learns what humans do using data, while other AI techniques may need human help. ML is the field of study that gives computers the ability to learn without being explicitly programmed (Samuel, 1959). Instead of humans teaching the computers the do's and don'ts, Samuel (1959) thought it might be possible to teach machines to learn for themselves. ML uses algorithms to detect patterns from a large set of data (Bellam, 2018). The patterns are used to predict future data or perform other kinds of decision making under uncertainty (K. P. Murphy, 2012). Another example of this is face recognition programs, where humans at first write the name of the people pictured. The algorithm then builds a model that can, in the same way as the human, determine who appear in which picture. When the accuracy level is high enough, the machine is considered to have learned what the people look like.

In practice, ML involves programming computers to learn from example data or past experience (Agrawal, Gans, & Goldfarb, 2017). It is self-learning, meaning it becomes smarter over time and allows the solution to adapt to changes without continuous investment or training effort (Bellam, 2018). To clarify, if you use an algorithm to predict something this is not necessarily considered ML. However, if you use the prediction to improve your algorithm further, it is. ML can be applied to nearly everything, as long as the data applied contains relevant information (Roßbach, 2017). Understanding ML is crucial in the process of understanding how a prediction is made and even what a prediction is.

To summarize; we see that with the IoT, collecting data is easier and large volumes of data are generated. Big data uses all feasible data, the information is made analyzable and one can detect patterns and knowledge from it. With AI, using ML algorithms, we can make predictions from these large data sets, and one is able to translate data to insight.

3.2 The Process from Data to Decision

In recent years, one has seen significant improvement in ML. Previously considered inherently human problems can now be done by machines. As ML improves, prediction gets easier (Marr, 2018). Economist think of this as a drop in the cost, and consequently the price will drop as well (Nickisch, 2018). In that way AI technologies improve the process of producing predictions and make them cheaper. This will cause more predictions and the use of prediction in undiscovered places. A market of prediction emerges, and in order to benefit from the new, arising business opportunities, the pricing of prediction is at the core. In the further we will elaborate prediction in the process from data to decision. We aim to clarify what predictions are, to facilitate for justified pricing decisions.

> *"Prediction is the process of filling in missing information. Prediction takes information you have, often called "data", and uses it to generate information you do not have"* (Agrawal et al., 2018).

The translator program fills in missing information, translating a sentence to another language. The program takes information you have, data of how words and sentences have been translated previously and uses this to generate information you do not have; the sentence you typed in another language.

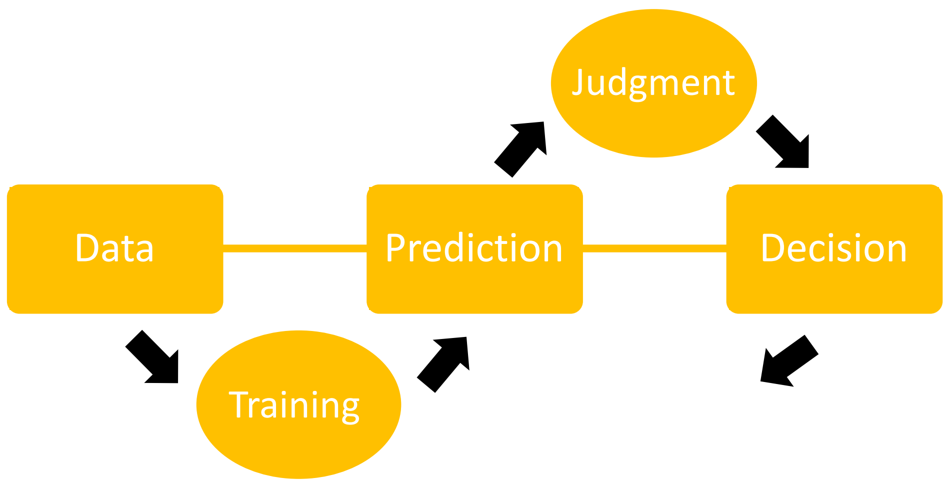

Figure 10 –The Process from Data to Decision, Based on Agrawal et al. (2018) and Kleinberg, Lakkaraju, Leskovec, Ludwig, and Mullainathan (2017)

The process presented in *Figure 10* shows the steps of transforming raw data into information used in decision making. In the link between data and prediction, we start out with a data set. There is a variety of different types of data that can be used, ranging from the number of sales to questionnaires. Using this data, we train a machine learning algorithm, enabling it to detect patterns. Training comprising learning about relationships between different types of data and which data is closely associated with a situation (Agrawal et al., 2018, p. 64). The patterns detected are used to predict the future, and we now possess a prediction. In the next step in the process, the decision maker combines judgment on what matters with the prediction. At this point, predictions translate to decisions (Kleinberg et al., 2017). It is in in the last step of the process, in prediction's ability to influence decisions, they acquire value (A. Murphy, 1993). Illustrated by the arrow in the model, the observed outcome can provide feedback to help improve the next prediction, enabling the algorithm to become smarter over time.

The process can be illustrated by an example presented by Agrawal et al. (2018, pp. 64-65), considering a doctor's appointment. The doctor starts taking tests, an X-ray and a blood test, in addition to asking questions. The doctor is gathering data, consistent with the first step of the model. We can consider this data trained using years in medical school and similar patients. The doctor is able to make a prediction: "You most likely have muscle cramps, although there is a small chance of a blood clot". Before deciding on the treatment, the doctor applies judgment. The doctor's intuition and experience are used to determine the relative payoff associated with each possible outcome. Suppose that in the case of a muscle cramp the treatment is rest, while if a blood clot a drug is needed. The drug has no long-term side effects, but it causes mild discomfort. Mistakenly treating muscle cramp with blood clot treatment results in some discomfort for a short time. Mistakenly treating the blood clot with rest results in a chance of serious complications or even death. The payoffs must be assessed, illustrating how the doctor apply judgment to the prediction. The doctor then makes a decision: "You should have treatment for the muscle cramp, even though there is some likelihood you have a blood clot". Administering the treatment and observing the outcome, the doctor can improve his prediction in the future.

3.3 The Characteristics of Predictions

Chosen characteristics of predictions are presented in the following. We do not elaborate on the variety of prediction techniques and the details of the mathematics behind them but instead, focus on the characteristics of predictions. We aim to create an understanding of the features of predictions and its importance for business purposes in order to later match these with pricing models.

3.3.1 **Judgment**

According to Kleinberg et al. (2017), predictions by themselves provide little value. Uncertainty is reduced by prediction, but the judgment is what assigns value (Agrawal et al., 2018, p. 18). Understanding the link between prediction and decision is at least as important as understanding the link between data and prediction, while applied work in machine learning typically focuses on the latter (Kleinberg et al., 2017).

We will continue to see human judgment being displaced by computers, but we will also see more and more syntheses of human judgment and computers (Tetlock & Gardner, 2015). An example of this syntheses could be the chess grandmaster Garry Kasparov and Deep Blue working together, where Kasparov draws from the strength of the computer with the possibility to override the computer. While an algorithm often beats the average expert, Gould-Davies (2017) argues one find the strongest performances when humans use data intelligently. This implies that the data does not speak for itself: it needs human interpreters. Tetlock and Gardner (2015) state that combinations of both humans and machines are more robust than pure-human or pure-machine approaches. In other words, one should devise techniques that bring human judgment and technological process to bear in a meaningfully balanced manner (Ekbia et al., 2015).

According to Boyd and Crawford (2012), interpretation is at the center of data analysis. Regardless of the size of the data, it is subject to limitations and bias and if these are not outlined and understood, there is a chance of misinterpretation. The quantity of information is increasing with several quintillion bytes per day, but the majority of it is noise and not useful information (Silver, 2012, p. 13). When the ratio of distracting noise to a useful signal is rising, the data does not speak for itself and needs human interpreters (Gould-Davies, 2017). Data analysis is most effective when researchers take into account the complex methodological processes underlying the analysis of the data (Boyd & Crawford, 2012). It is first when the role of predictions in decision making is made clear that predictions become useful (Kleinberg et al., 2017). A. Murphy (1993) states that predictions possess no intrinsic value on their own, they acquire value through their ability to influence decisions.

3.3.2 Evaluation

Predictions aim to generate information you do not have, based on the information you have (Agrawal et al., 2018). While trying to predict the unknown, evaluating the value of predictions is both important and challenging. In the following, we will consider different aspects of how predictions are evaluated, and difficulties connected to these.

Missing data

The production of predictions depends on input data. In the case of missing data, data is missing for some variables and for some cases, which is a problem because it violates the assumptions of statistical methods (Allison, 2002). One type of missing data problem is the selective label problem, which occurs when the judgment of a decision-maker determines which instances have labels (Lakkaraju, Kleinberg, Leskovec, Ludwig, & Mullainathan, 2017).

Lakkaraju et al. (2017) exemplify selective labeling in the decision of judicial bail. The outcome of whether a defendant fails to return for their court appearance will only be observed if the human judge decides to release the defendant on bail. When the defendant is not released, we do not know whether he would appear in court or not if he had been released. The outcomes which are observed do not represent a random sample of the population.

As the data does not represent what could have happened with a different decision, one is not able to measure the differential effects of different actions (Dhar, 2013). Machine learning analyses tend to ignore this problem, but without resolving this challenge, it is hard to compare human decisions to algorithmic predictions (Kleinberg et al., 2017). In summary, the selective label problem makes it harder to evaluate predictions (Lakkaraju et al., 2017).

There is also an issue of data error. Large data sets are often prone to outages and losses, and even if the data sets are large they are not necessarily random or representative (Boyd & Crawford, 2012). Errors and gaps are also magnified when multiple data sets are used together.

Criteria

We now consider the last part of the process model in *Figure 10.* After judgment is applied to your prediction and the decision is made, one evaluates the output. There is a number of different methods used with different technical skill levels required. We present an overview of some of the methods used including critics against them, without considering techniques to perform them in practice.

A. Murphy (1993) highlights three methods where different criteria can be assessed to define what is, and what is not, a good prediction. The first method presented is quality: The correspondence between predictions and observations. The quality can be measured using different evaluation metrics, where accuracy is frequently used (Kononenko & Kukar, 2007). The level of prediction accuracy is defined by the degree of similarity between the training data and the test data, by means of the similarity between the data used to fit and test the model (Baldi, Brunak, Chauvin, Andersen, & Nielsen, 2000).

What is problematic with accuracy as a measure is the fact that predictions with the same accuracy can be seen as unequally good (Goodman, 1952). Studying 100 parolees Goodman (1952) used two different factors predicting the number of parolees that would and would not violate the parole. The two predictions have the same accuracy. One states that parolees would violate when they in fact did not. The other states that parolees would not violate when they in fact did. As most people would agree, failing to prevent a violation is worse than paroling a non-violator. One prediction is better than the other and accuracy as a measure should be used with caution.

Being confident on the accuracy of predictions is crucial for those making decisions based on predictions after either paying or creating them (Gould-Davies, 2017). In regard to the use of predictions in business, an efficient future industry should according to Gould-Davies (2017) reward good predictions and punish bad ones.

Second, A. Murphy (1993) presents consistency: The correspondence between predictions and judgments. Considering the process from data to decision (*Figure 10*), measuring using consistency assumes that the producer of the prediction applies judgment before the sale, selling a decision as opposed to a prediction. Since the measure is under the control of the predictor, it is possible to achieve very high levels of consistency by making the predictions correspond with one's judgment (A. Murphy, 1993).

The last method presented is value: The incremental benefits of predictions to users. Value relates to the benefits realized or expenses incurred when a prediction is used in decision making. A. Murphy (1993) presents four determinants to assess the value of predictions identified by Hilton (1981): (i) the courses of action available to the decision maker, (ii) the payoff structure associated with the decision-making problem, (iii) the quality of the information used as a basis for decision making in the absence of the predictions and (iv) the quality of the predictions. The value will vary between different problems and different users, hence the predictor will need user-specific information to achieve the highest possible value (A. Murphy, 1993).

4. Pricing of Predictions

In order to understand how to price predictions, we will in the following use presented pricing theory together with identified characteristics of predictions. By reviewing each of the previously presented pricing models, we aim to create a better understanding of how these can be used. The analysis results in a decision model for the pricing of predictions.

We target the businesses developed to sell predictions as their core business. In the future, this might apply to several companies that today sell a physical product but gather data and discover new and more profitable ways. Telenor sells products such as cell phones and cell phone plans today. Gathering large amounts of data and working with new AI technologies, they now experiment with business model innovation and alternative ways to do business in the future.

We assume that the predictions are sold externally, they are produced for resale and not to optimize one's own operation. Additionally, the predictions are sold without judgment applied, leaving this part of the process to the buyer. We analyze from a seller's point of view, based on a long-term customer relationship.

4.1 Unit-based pricing

Unit-based pricing involves paying a fee to a solution provider dependent on the utilization within a given time period (Bonnemeier et al., 2010), and can possibly be applied at predictions. Prediction is the process of filling in missing information (Agrawal et al., 2018) and allowing the user to utilize the solution as time goes can be advantageous for the customer. The growth of cloud storage and computing has increased application of usage-based pricing (Balasubramanian et al., 2015), and these technological developments might facilitate usage-based pricing of predictions. We will consider both usage-based and measure-based pricing of predictions in the following.

Judgment

Kwortnik et al. (2006) present unit-based pricing in the grocery industry. Selling physical products one can see a clear distinction between what is categorized as measure-based and usage-based unit pricing. Using laundry detergent as an example, a measure-based price would be expressed in kilos, while a usage-based price in the number of wash loads. Considering the complexity of predictions, especially the need for the application of judgment, this distinction might not be easily transferable. Measure-based pricing of predictions would use a metric for size; kilobyte (KB), megabyte (MB), gigabyte (GB) or terabyte (TB). Usage-based pricing would use a metric for use, equivalent to the number of wash loads one could use the number of predictions. Kwortnik et al. (2006) find the benefit of usage-based unit pricing is increasing consumers' ability to identify product value, but a metric of the number of predictions barely contributes. For this pricing model, a metric like the number of decisions would better serve the purpose of clarifying the product value of predictions. Measuring how many predictions needed for a decision is far more complex than measuring how much detergent is needed for a wash load. The number of predictions needed for a decision is dependent on judgment and factors outside the seller's control, complicating the use of usage-based pricing for predictions.

Bonnemeier et al. (2010) present usage-based pricing of solutions, which is customized integrations of goods and services. To exemplify, this could be pricing dependent on the usage-time of a consultancy service, or the intensity of hardware support. This approach to the model illustrates in a better way than the selling of laundry detergent how usage-based pricing can be applied at predictions. The difference is that solutions might come with judgment. We sell an estimated guess about the future which later is assigned judgment. One can measure the usage-time or intensity of the use of predictions. Nevertheless, the challenge of finding a suitable metric is still relevant.

The need for judgment before decision making complicates the process of selling predictions. One could argue that the buyers of predictions were a few, large companies with high technical competence, able to apply judgment and profit from good decisions on this basis. As there is a wide range of predictions, with a different degree of judgment needed, this does not have to be true. When predictions in addition become cheaper and more accessible, we cannot even exclude the local, vegan food truck as a potential buyer. For the pricing decision one must consider whether one has to do with high- or low-frequency users. The firm will be more likely to charge a usage price if the heavy users are more valuable to the firm than light users (Altmann & Chu, 2001), since revenue using usage-based pricing depends heavily on the frequency of use (Balasubramanian et al., 2015). In the case of predictions, heavy users are to be considered buyers who frequently buy and demand updated predictions. Considering the buyer side, it is according to Altmann and Chu (2001), the low-frequency users that prefer usage-based pricing.

Applying this pricing model might attract customers that do not intend to have frequent use of the predictions.

Evaluation

The evaluation of a prediction is conducted by the buyer, which can involve using either the quality, the consistency or the value to define a prediction as good or bad. Evaluating predictions is difficult (A. Murphy, 1993), therefore the buyer might be unable to identify the actual perceived value from the prediction. The seller runs a risk of good predictions being evaluated as bad. A pricing model that considers this would be advantageous. One can then make a higher profit as a seller, as the buyer sees or utilizes the actual value of the prediction. In the following, we will investigate how the unit-based pricing can affect the evaluation of predictions.

The evaluation of predictions might be easier as one can see more clearly the connection between each prediction and each decision. The buyer then continues to purchase the accurate or the high-value prediction and stops using the predictions that do not lead to better decision making. In that matter, one can argue that unit-based pricing stimulates to reward good, and punish bad predictions, as Gould-Davies (2017) emphasizes. The prices, in the long run, would reflect which predictions are good, and which are not. However, the evaluation is complicated as value depends on judgment applied, which are outside the seller's control.

To further complicate the issue of evaluation, the value of a prediction is determined by Hilton's four determinants (1981). Three of them are (i) the different options of the decision maker, (ii) the payoff structure related to these options and (iii) the information the buyer has in absence of the prediction. The seller is not in control of these and does not necessarily possess any information about them. It would require thorough information of each customer to analyze what is really causing the customers demand.

Usage-based pricing might attract low-frequency users (Altmann & Chu, 2001). These users might to a smaller extent have the capacity, including human knowledge and necessary systems, to properly be able to evaluate the prediction. If so, good and bad predictions are not reflected in prices and demand. This would make it harder for you to make a profit. One might be lucky and profit from a bad prediction, but there is a chance that you miss profit from a good prediction. We emphasize the importance of transparency, and to make money on quality. Either way, one must consider the capacity of the customer to properly evaluate your prediction.

4.1.2 Sub-conclusion

Unit-based pricing gives the buyer a price at the time of purchase and allows differentiation in price between predictions. While the cost of measuring is no longer considered as big a problem due to recent progress in technology, choosing appropriate metrics in the case of predictions is. Businesses should establish whether their customers are heavy or light users and be aware that unit-based pricing does not take into account the difficulties of evaluating predictions.

4.2 Subscription-based pricing

Subscription-based pricing allows for unlimited consumption during a specific period of time (Nahata et al., 1999). Thus, pricing with a subscription-based structure is independent of usage (Sundararajan, 2004). As one avoids the large costs and difficulties associated with both measuring the use and evaluating the performance of predictions, subscription-based pricing might be the preferred pricing model for prediction pricing.

4.2.1 Flat-fee

In regard of flat-fee pricing of predictions, the buyer will in exchange for a fee, get unlimited access to all available predictions for a specific time period. Flat-fee pricing is gaining customer preference (Hinterhuber & Liozu, 2014), and we will in the further considered this as a possible pricing model of predictions.

Judgment

By presenting a flat-fee, the buyer is left with no uncertainty concerning price, which is argued to be preferred by customers (Train, 1991, p. 211). Considering predictions bought for business purposes, they acquire value through their ability to influence decisions (A. Murphy, 1993). Added judgment, and value created when predictions are used in decisions, is not reflected in the price, when using a predetermined flat-fee.

Even though neither added judgment nor created value is considered in the price, a flat-fee has its benefits in the pricing of predictions. If we are to compare unit-based pricing with flat-fee, they both present a price at the time of purchase, leaving no uncertainty regarding price. Considering the fact that the predetermined price is not considering judgment, the buyer can be assumed to be somewhat ignorant regarding what one might get out of buying a prediction. A pricing model allowing the buyer to try using different predictions without additional cost might be of great value. Building further on this we consider the psychological cost of the buyer of predictions. If the psychological cost associated with buying is high, flat-fee pricing should be used (Balasubramanian et al., 2015), simplifying the payment process for the buyer. In the case of predictions, if a buyer was to buy more than just a few predictions on a regular basis, the psychological cost would be considered high. If a buyer was to go through a payment system, for example by adding predictions to a shopping cart and entering billing information every week or month, this would be psychologically costly. Uncertainty as to which predictions are relevant and the potential permanent use of predictions can result in high psychological costs, favoring flat-fee pricing of predictions.

To a larger degree than with the use of other pricing models, customers are suggested to be comfortable with automated and direct changes, using flat-fee pricing (Sundararajan, 2004). Building on the previous discussion about judgment, the ability to easily and unproblematically change prices might be considered a big advantage in the pricing of predictions. Judgment assigns value to the predictions (Agrawal et al., 2018, p. 18) and as the use of the prediction impact the value, the value might vary. This could lead to a desire to change prices accordingly. Using a flat-fee the seller can, without much effort, adjust the price according to variations in the experienced demand for predictions. Additionally, one does not have to set individual prices for each prediction.

Evaluation

One might argue that a pricing model considering perceived value after judgment and decision-making is of preference pricing predictions. However, because of the difficulties experienced evaluating predictions (A. Murphy, 1993), this might not be the case. As subscription-based pricing sets a flat-fee, this pricing model avoids the problem of the seller's evaluation of prediction value. The result of this is a simple pricing model to implement and operate for sellers of predictions, but also a pricing model easy to understand for buyers of predictions.

As for Gould-Davies (2017) thoughts what matters an efficient future industry for predictions in business, this pricing model is not able to reward good predictions and punish bad ones. Since the customers are offered unlimited consumption for a fixed price, the predictions offered and made available are not differentiated when it comes to price and value. Thereby, the pricing model subsidizes heavy users at the expense of light users (Essegaier et al., 2002). In the failure to reward good and punish bad predictions, one might risk losing light users to rivals when using flat-fee pricing (Essegaier et al., 2002).

4.2.2 **Two-part tariff**

A two-part tariff is a pricing model that combines usage-based pricing and a flat-fee (Essegaier et al., 2002). The flat-fee can be considered an entry fee, whilst the usage price will apply for any level of usage. In terms of applying this pricing model on predictions, it either has to bring along new features that are beneficial or prevent the negative features of usage-based or subscription-based pricing, in order to be preferred in favor of either of the two.

Judgment

Building on the discussion of heavy and light users in section 4.1 about unit-based pricing, the need for judgment application before decision making can make it likely for a greater part of the buyers to be both big and tech-heavy, resulting in few buyers with high-frequency use. As this is not necessarily the case, whether one has to do with high- or low-frequency users must be considered by the seller. A pricing structure that is organized as a two-part tariff makes the seller vulnerable to lose both heavy and light users to rivals (Essegaier et al., 2002). Using flat-fee pricing efficiently involves subsidizing heavy users at the expense of light users, where those using predictions only a little pay for the use of those using them a lot. Using a two-part tariff in the pricing of predictions, one allow for others to steal the light users. As heavy users benefit from a flat-fee (Essegaier et al., 2002), and light users prefer usage-based pricing

(Altmann & Chu, 2001), the flat-fee pricing risks losing the preference from both of these customer groups and will be unfavorable independent of which user-group is the most valuable to the firm.

Evaluation

With a two-part tariff you have the disadvantage of costs carried by monitoring usage and assigning value to each prediction, compared to flat-fee pricing where this is not needed. Flat-fee pricing was considered a good fit for pricing of predictions, as it to some degree avoids the problem of the seller's evaluation of prediction value. We see this beneficial since the evaluation of value is considered especially difficult for predictions. This advantage does not hold for two-part tariff pricing, because one must price each prediction individually. We cannot exploit the benefits of flat-fee pricing and would not prefer two-part tariff pricing over flat-fee pricing of predictions.

4.2.3 **Bucket pricing**

Both bucket pricing and two-part tariff pricing use a fixed fee. The difference between the two lies in whether the fixed fee is dependent on usage or not. Pricing with a two-part tariff involves a usage-independent fixed fee (Schlereth & Skiera, 2012). The buyer pays for the right to access or participate, and the fixed fee does not include any use. For bucket pricing, the fixed fee involves free use up to a certain level (Iyengar et al., 2008). The fact that bucket pricing based on this retain more elements from flat-fee pricing than two-part tariff pricing might make it a better choice for the pricing of predictions.

Judgment

Bucket pricing encounter consumers to use a pre-set number of units, unlike usage-based pricing, flat-fee pricing and two-part tariff pricing (Schlereth & Skiera, 2012). This pricing model can therefore be considered less flexible in terms of volume purchased than the previously mentioned models. For a bucket including 100 predictions, consuming the 101st prediction would be a more judicious consideration than consuming the 101st prediction under usage-based pricing. In this manner, bucket pricing can be perceived as restrictive. In addition, when considering to buy the first prediction, bucket pricing forces you to buy 100 predictions, while usage-based pricing allows you to buy only one.

The role of judgment makes the value of predictions vary to a large extent (A. Murphy, 1993). Since the buyer will have to interpret and use the prediction wisely in decision making, the value of the prediction is difficult to determine at the time of purchase. Considering buying furniture as an example, we compare IKEA and high-end furniture providers. While IKEA depends on the customer doing part of the work by assembling the furniture, high-end providers deliver the product in whole, already assembled at your door. How the customer assemble the furniture could potentially affect the product. To a greater extent, but still transferable, buying a prediction leaves you with risk as to what value you will receive due to the usage of it.

Due to this uncertainty regarding received, one can argue the need for a flexible pricing model. Since value is dependent on judgment, we can assume one finds it hard to know how many and what kinds of predictions are needed at the time of purchase. Given this, bucket pricing might prevent buyers from buying additional predictions, despite the fact that they want them, due to the restricted use. Where the previously presented pricing models encourage and facilitate additional sales, bucket pricing might be considered less suitable pricing predictions from a seller’s point of view.

Evaluation

Discussing the use of flat-fee pricing of predictions, not having to evaluate and assign a value to each prediction were highlighted as an advantage, due to the difficulties of this process. In bucket pricing, the seller charges a fixed fee and allows free use up to a certain level, beyond which consumers must pay a usage-based unit rate (Iyengar et al., 2008). This pricing model thereby neither evaluate nor take into consideration perceived value from using predictions, pricing the actual bucket. What separates them is that bucket pricing limits the access to a pre-set number of units (Schlereth & Skiera, 2012), while flat-fee pricing allows unlimited access. For usage above the included amount of the bucket, bucket pricing seems to carry the same costs as usage-based pricing related to measuring usage. Consequently, bucket pricing does not seem to be able to avoid the problem of the seller evaluating the perceived value, having to set prices if buyers are to buy predictions beyond those included in the bucket.

4.2.4 **Sub-conclusion**

All of the presented subscription-based pricing models demand a fixed fee in order to access the predictions. They differ from one another in what the customer receives in exchange for this fixed fee. The flat-fee pricing model allows unlimited consumption during a specific period of time for the fee (Nahata et al., 1999). The two-part tariff demands the fixed fee in order to buy and requires payment dependent on any usage (Essegaier et al., 2002). In bucket-pricing, the fixed fee allows free use up to a certain level, beyond which consumers must pay a usage-based unit-rate (Iyengar et al., 2008). They differ from the other presented pricing models in the degree to which they require measuring of usage.

4.3 Output-dependent pricing

In recent years, the literature seems to move the focus of pricing away from cost, and rather towards models that are more oriented on perceived customer value (Bonnemeier et al., 2010). In order to set prices that reflect the actual value received, one has to understand what creates meaningful value for different customers (Nagle & Hogan, 2006, p. 18). Applying this on the case of predictions, one has to understand how predictions create value. Predictions reduce uncertainty but provide little value by themselves (Kleinberg et al., 2017). As judgment is considered the factor assigning value to the predictions (Agrawal et al., 2018, p. 18), output-dependent pricing might prove to be a well-suited pricing model. Due to its ability to include perceived value as a decision metric when deciding price, the value generated when adding judgment and when making a decision based on predictions will be taken into consideration. This might make output-dependent pricing preferred over other pricing models.

4.3.1 **Performance-based**

Performance-based pricing is one of several models used to determine prices on the basis of output (Bonnemeier et al., 2010). Recent advances in technology simplify gathering and making sense of data. This enables the process of evaluating performance to be simplified, which may further lead to an increase in the use of performance-based pricing.

Judgment

In performance-based pricing, the seller is paid depending on the performance outcome determined together with the customer (Hinterhuber & Liozu, 2014). Considering the fact that a prediction by itself has no intrinsic value and create value first when added judgment and used in decision making (A. Murphy, 1993), determining price together with the customer can be beneficial. To exemplify, two parts can agree on a price of $20,000 for the predictions to increase sales by 20%. If sales only increase by 10%, the buyer and the seller agree on a price reduction. By pricing together, the value added in the process of judgment is considered, which is how much the sale is increased. This facilitates the price to reflect the real value of the prediction, to a greater extent than with other pricing schemes.

For prediction purposes, a performance-based pricing model will negotiate prices at the point of time when the prediction is handed over, but if the prediction is to perform poorly this can result in penalties and a reduction of the pre-negotiated price (Turner & Simister, 2001). The buyer will only know the maximum price in advance and by this having to hold uncertainty regarding the final cost until after we observe actual sales (Nagle & Hogan, 2006, p. 57). Further, the evaluation to which degree the prediction performed will rely on judgment. In practice, the seller can provide a good prediction, but if the buyer is not able to exploit the value from it applying judgment and making decisions, the goal of 20% increase in sales might not be reached. This due to factors beyond the control of the seller. Since we consider businesses selling predictions and not predictions together with judgment, the seller of predictions is left with great risk using performance-based pricing. On the positive side sharing of risk contribute to making the product more affordable for the buyer (Piercy et al., 2010). In summary, the price depending on the judgment in performance-based pricing causes uncertainty.

Evaluation

As predictions aim to generate information you do not have based on the information you have (Agrawal et al., 2018), evaluating a prediction can be considered to be a valuation of an estimated guess. By allowing us to adjust the price after acting on the information presented by the prediction, the price will reflect benefits realized or expenses incurred. This coincides with what A. Murphy (1993) imposes in value as an evaluation metric.

With performance-based pricing one agrees on a guarantee, a goal we must achieve, in advance of the sale. This could typically be benefits realized or expenses incurred, like the 20% increase in sales. Exactly these metrics, benefits and expenses are recommended to evaluate predictions (A. Murphy, 1993). Predictions are particularly suitable in this regard.

Nevertheless, pricing based on performance requires information from the buyer, which comes together with trust in the fact that the buyer actually reports accurate information (Nagle & Hogan, 2006, p. 57). In order to actually be a suitable pricing model, the user-specific information must be credible. Further, due to the large need for monitoring, there are large costs related to performance-based pricing (Hinterhuber & Liozu, 2014). The pricing model will make it possible to reward good predictions and punish bad ones, assuming that the evaluation is done correctly, which is considered an important feature for an efficient future industry using predictions in business (Gould-Davies, 2017).

4.3.2 **Value-based**

Another model used to determine prices on the basis of output is value-based pricing (Bonnemeier et al., 2010). While performance-based pricing pre-negotiates a price that later can be reduced (Turner & Simister, 2001), value-based pricing is solely based on value created by the implementation of the proposed solution (Sawhney, 2004). Consequently, a value-based price might be a percentage of cost savings realized when buying and implementing predictions in decisions. A performance-based price in the same situation would be determined before buying and implementing the prediction, and then be an object to a potential reduction depending on the prediction performance. As value-based pricing allows us to determine the price in full after the point when performance can be evaluated (Hinterhuber & Liozu, 2014), this pricing model might be preferred in the pricing of predictions.

Judgment

Value-based pricing focuses on the customer's internal processes by delivering optimization or productivity (Bonnemeier et al., 2010). For prediction purposes the pricing based on this pricing scheme would be based on values like the amount of cost savings generated by buying the prediction, adding judgment and using it in decision making (Sawhney, 2004). In value-based pricing, the seller thus directly benefit from the value added by the prediction (Hinterhuber, 2004). Considering the fact that predictions alone have no intrinsic value (A. Murphy, 1993), generating the price on the basis of the value it adds after judgment and decision making will enable the price to reflect the buyers perceived benefits.

Similar to performance-based pricing, also value-based pricing considers judgment and decision. The final price is not determined until value from using the predictions is perceived and measured. Contrary to performance-based pricing, value-based pricing does not pre-determine a price, but instead solely price based on value generated after decision making (Sawhney, 2004). This value incurs from the bought predictions and the judgment applied. Pricing based on value allows customers to add judgment and use it in decision making before pricing, giving time to reveal the true value perceived from buying the predictions and set a price accordingly (Ingenbleek, 2007). Thus when buying predictions, customers trade off advantages from buying the predictions against the uncertainty of price (Ingenbleek, 2007). The price depends on the judgment added and further decisions made on the basis of this.

Evaluation

Predictions are evaluated in different ways, all with different faults and pitfalls (A. Murphy, 1993), illustrating the difficulties related to evaluating predictions. One of the criteria presented by A. Murphy (1993) is value, considering benefit realized or expenses incurred when a prediction is used in decision making. These are examples of values the value-based pricing scheme base pricing on (Sawhney, 2004). As the value will vary from problem to problem and user to user, the predictor will need user-specific information (A. Murphy, 1993). The literature presents barriers in the market to adopt value-based pricing, where one of these is the challenge of objectively measuring value created (Sawhney, 2004). Even though value-based pricing allows us to set the price after implementation, we will experience the same evaluation problems measuring value as for predictions alone. The need for user-specific information complicates an objective measure of value created.

As value-based pricing sets the price by solely measuring value after implementation (Bonnemeier et al., 2010), it enables the opportunity to match perceived price with perceived benefits. Literature finds that when customers perceive that they pay a good price for the obtained benefits, this can increase their purchase intentions (Grewal et al., 1998). Considering that predictions are estimated guesses, obtained benefits are harder to identify. A pricing model that forces the buyer to identify obtained benefits will be favorable. To clarify, if a seller of predictions practices this pricing model, he forces the buyer to see the benefits of a product which are hard to evaluate. This can lead to increased sales.

4.3.3 Quality-contingent

Quality-contingent pricing is presented in the literature as a pricing model based on output metrics related to quality (Bhargava & Sundaresan, 2003). This pricing model has similarities to performance-based pricing presented by Bonnemeier et al. (2010). Quality-contingent pricing also determines levels of pricing before perceived value can be measured, in addition they both guarantee a level of performance. The difference between the two lies in the way to adjust their prices after measuring performance. While performance-based pricing in the event of poor performance either reduces prices or receives penalties to levels decided after evaluation of performance (Turner & Simister, 2001), quality-contingent pricing sets a pre-announced rebate for poor performance (Bhargava & Sundaresan, 2003). Using this kind of output-dependent pricing might, by this reason, reduce the uncertainty and risk held by the buyer of predictions, and be a preferred pricing model.

Judgment

Quality-contingent pricing sets a pre-announced rebate for poor performance. Instead of setting a single price, one announces quality-price pairs for various levels of quality (Bhargava & Sundaresan, 2003). As predictions are difficult to evaluate (A. Murphy, 1993), quality-contingent pricing might be a suitable pricing model that enables matching the perceived benefits from use with the price of predictions. However, the features of predictions might suggest otherwise as quality-contingent pricing works well when quality is objectively verifiable and unaffected by use (Bhargava & Sundaresan, 2003). As predictions on their own only reduce uncertainty and assign a value when used together with judgment (Agrawal et al., 2018, p. 18), to objectively verify the quality of predictions will prove difficult. Nevertheless, the quality of predictions can under no circumstances be unaffected by use, as the data does not speak for itself and need human interpreters in judgment (Gould-Davies, 2017).

Biyalogorsky and Gerstner (2004) present contingency contracts in their literature review of quality contingent pricing. They say these contracts rely on the fact that the buyer often purchases either products or services before the anticipated consumption. This is transferrable to the situation of selling predictions, where the customer buys the prediction ignorant as to what insight might be the result. Since judgment must be applied before one can use the insight of predictions in decision making, pricing contingent on quality might be the preferred pricing model. With the use of contingency contracts, outcomes contingent on a realized future can be specified, avoiding missing out on a potential deal because of disagreement as to the likelihood of future events (Biyalogorsky & Gerstner, 2004). In a situation where the prediction seller and -buyer disagree what matters potential output from buying the specific prediction, quality-contingent pricing might enable an agreement between the two, while other pricing models might not.

Evaluation

Pricing contingent on quality is found to be especially well-suited for IT services (Bhargava & Sundaresan, 2003). As this is due to their ability to quantify, capture, verify and disseminate quality, this is not applicable for pricing of predictions. These features of IT are not features of predictions and the pricing model cannot be said to fit well on the basis of its suitability for IT services. Features of predictions make them difficult to evaluate (A. Murphy, 1993), unlike IT services.

The pricing model is useful in situations where the market underestimates the firm's performance (Bhargava & Sundaresan, 2003). Based on our understanding, this applies to all the identified output-dependent pricing models. Can the performance of predictions be underestimated? In recent years advances in big data and technology have allowed us to efficiently process massive amounts of data in addition to extracting value from it (Zaslavsky et al., 2013). This combined with IoT making data gathering both easy and effortless (De Cremer et al., 2017), might have resulted in a better predictions than what is the general understanding amongst customers.

Large data sets are often at risk of outages and losses, and even if the data sets are of a great size they are not necessarily random or representative (Boyd & Crawford, 2012). Not to mention the fact that the data can be missing information that we cannot measure (Lakkaraju et al., 2017). These are additional factors that bring uncertainty to the quality of prediction and can further complicate the evaluation. The poor prediction can both be caused by an unrepresentative data set or poor judgment applied. Quality-contingent pricing has great potential value when pricing under quality uncertainty (Bazerman & Gillespie, 1999). Since predictions are of changing quality, this pricing model might be preferable.

4.3.4 **Sub-conclusion**

Output-dependent pricing enables the opportunity to include perceived value as a decision metric, resulting in a price including value generated when adding judgment and when making decisions based on predictions. Performance-based pricing sets a price before selling and adjusts this by reduction or penalties, depending on how the prediction performs. Value-based pricing decides price after decision making on the basis of created value. Quality-contingent pricing announces both price and potential rebate before selling. Considering the presented literature, all presented models consider output from using predictions in decision making in their price, distinguishing the three is the uncertainty carried by the buyer. While the buyer knows all possible prices with quality-contingent pricing before buying, it is unaware of the price level with value-based pricing. Considering performance-based pricing the buyer has a basis in the pre-negotiated price but is ignorant regarding the final price as potential benefits will be decided after evaluation. In a review of these models compared to others, the difficult task of evaluating predictions must be considered.

4.4 Pricing Model

The analysis of prediction pricing is applied to create a decision model. The model is thought to assist decision-makers in businesses and will be helpful in the choice of how to price a prediction. The model emphasizes the willingness to pay for each prediction, meaning the importance and value of the prediction at the time of purchase. The degree of judgment necessary to create value with the prediction is also considered, meaning the degree of how complicated or crucial the judgment is to create value using the prediction.

The process from data to decision, including judgment, causes difficulties to the evaluation. The higher the degree of judgment applied, the harder the evaluation might be. To clarify we consider a baking example. If the finished cake is dry, it is hard to determine whether this is due to you adding too little butter or baking it too long, or due to the baking mix and recipe. Determining who to blame just became much more difficult than when buying a finished cake or at least a baking mix with fewer steps. Additionally, the perception of what is a dry cake might vary.

The degree of difficultness evaluating the prediction is not considered in the model. We have discussed how the difficulty of evaluating the prediction complicates the use of the presented pricing models. None of the models could be excluded on this basis. In the choice of pricing model, the evaluation aspect needs to be kept in mind. This certainly applies to output-dependent pricing.

Our model consists of four states, dependent on the willingness to pay and the judgment applied. For each state unit-based pricing, subscription-based pricing and output-dependent pricing is considered. This is presented in the following.

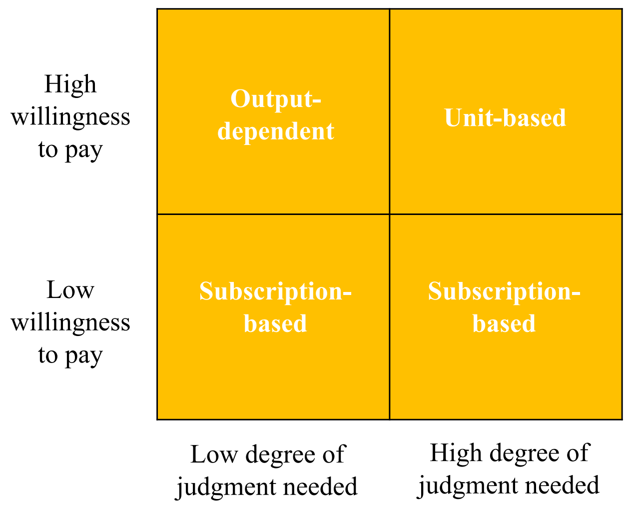

Figure 11 - Pricing Model for Predictions

4.4.1 **High willingness to pay – Low degree of judgment needed**

In this state each prediction is of high value to the buyer. We want the pricing model to reflect this. As the buyer has a high willingness to pay at the time of purchase, the seller should choose a pricing model to reflect this value. Subscription-based pricing fails to reflect high value for individual predictions, charging one price for a number of predictions instead of having a customized price for each prediction. On this basis we chose to exclude this pricing model.

When the output to a low degree is dependent on judgment applied by the buyer, the seller of this prediction carries low risk. This is because the real value of the prediction is less dependent on the buyer's application of judgment, compared to a prediction that needs a high degree of judgment. It is still possible for the value to change, but the risk is considered smaller. A unit-based price is determined at the time of purchase and does not necessarily depend on the final value of the prediction. Therefore, we exclude unit-based pricing.

We find *output-dependent pricing* beneficial, as the price reflects the value the prediction creates. In addition, the extracted value does not heavily depend on the application of judgment.

4.4.2 **High willingness to pay – High degree of judgment needed**

Due to the high willingness to pay, we still want to reflect the value of the prediction at the time of purchase and exclude subscription-based pricing.

Since we now find a larger degree of judgment needed, the seller runs a risk by using a pricing model that depends on the judgment. The buyer can end up receiving a lower price due to user error or a higher price due to expedient utilization. Whether output-dependent pricing should be chosen or not depends on the risk profile of the seller. We choose to exclude it, emphasizing the risk of a decreased value the most.

By this, we find *unit-based pricing* beneficial. We assume that a proper metric is found. The price will capture the high willingness to pay for each prediction, at the time of purchase. Additionally, the price will not depend on the judgment added allowing the seller to avoid carrying the associated risk.

4.4.3 **Low willingness to pay – Low degree of judgment needed**

Predictions will have different value for businesses. Therefore, it is reasonable to assume that a producer and seller of predictions will have predictions with low willingness to pay as well as high. From our literature review, we found that customers tend to pay more with subscription-based pricing compared to unit-based pricing. In a situation like this, where willingness to pay at the time of purchase is low, a unit-based price is likely to be low. Thus, the seller will not want to reflect this value in the price. Subscription-based pricing is preferred over unit-based, and we choose to exclude unit-based pricing.

A low degree of judgment needed leaves the seller with a lower risk regarding a price determined by output. Output-dependent pricing is feasible, but the question is whether it is desirable as this price will potentially be low. Willingness to pay at the time of purchase and in the time after can vary, but since a low degree of judgment is needed the value is likely to change minimally.

Subscription-based pricing is the preferred model as it might enable businesses to also profit on predictions considered being of less value.

4.4.4 **Low willingness to pay – High degree of judgment needed**

With a low willingness to pay one will still not want to reflect the value in the price at the point of purchase. A customer that does not see the value of a prediction, and hence has low willingness to pay, might find it beneficial to subscribe to many predictions. This allows him to explore and possibly see the potential value of prediction in a greater manner than with unit-based pricing. We choose to exclude unit-based pricing.

A high degree of judgment is needed, hence there is a risk associated with determining the price based on the output. To avoid running the risk of receiving a lower price due to user error in the process of applying judgment, we suggest avoiding the use of output-dependent pricing in this state.

From the seller's point of view, we find *subscription-based pricing* preferable in both states considering a low willingness to pay.

5. Managerial Implications

The purpose of this thesis is to elucidate the pricing of AI-based predictions. AI and predictions will affect most of our lives, and businesses as well. Data, often referred to as the new oil, is storing up. From which you can feed your algorithms and make predictions, and by this turn data into insight. Your business has two choices; either use them for internal growth and innovation or sell them externally and profit. For the latter, this can turn your business model upside down. Your pricing model is key for any business strategy. Therefore, we find it essential to elucidate the pricing of predictions. By combining literature about predictions` characteristics with an extensive literature search of pricing from 2000-2019, we answered the following research question:

How can pricing models of goods and services be used for the pricing of AI-based predictions?

From our literature review, we identified three main categories of pricing models. Unit-based pricing, subscription-based pricing, and output-based pricing. Unit-based pricing of predictions gives the seller the opportunity to differentiate the price between predictions, and the price is set at the time of purchase. Choosing an appropriate metric stands out as the pitfall of this pricing model. Additionally, the proportion of heavy to light users will most likely impact your profit.

Subscription-based pricing can either be arranged as a flat-fee, a two-part tariff or bucket-pricing. They all demand a fixed fee in order to access the predictions. The flat-fee stands out as the most favorable model. One is allowed unlimited consumption during a specific period of time, and the seller avoids the hassle of measuring usage. The customers appreciate the certainty of price, but the value perceived when judgment is applied might not be reflected in the price.

Finally, we identified three categories of output-dependent pricing. Performance-based, value-based and quality-contingent pricing all enable you to include the value generated by using the prediction in decision making. We see this as strongly favorable if suitable performance or value-metrics are found. In the choice of the three models, one has to consider the amount of uncertainty carried by the customer regarding price. By carrying some risk, the client base might expand.

Our decision model for the pricing of predictions is developed on the basis of our analysis. The issue of evaluating a prediction, different types of data, training and different types of decisions are not directly considered in the model. The model is limited to consider the willingness to pay for each prediction and the degree of judgment necessary to create value.

In the state of *high willingness to pay* and a *low degree of judgment needed,* we recommend applying *output-dependent pricing.* We profit from a high valued product, witch to a small extent depends on the application of judgment. When the *high willingness to pay* is combined with a *high degree of judgment needed* we argue a *unit-based pricing model* applicable. One avoids the price depending on the judgment, which is at risk of decreasing the value. The pricing also enables one to capture the high willingness to pay at the time of purchase. In the case of *low willingness to pay*, independent of whether a high or low degree of judgment is needed, we recommend *subscription-based pricing.* Your business is enabled to profit on predictions also considered of less value.

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Appendix

Search 1 – Subject: Thesaurus Term

- Pricing
- Prices
- Marketing
- Retail industry
- Consumer behavior
- Revenue management
- Consumers
- Decision making
- Marketing strategy
- Business enterprises
- Supply chains
- Markets
- Electronic commerce
- Profit
- Supply & demand
- Algorithms
- Price regulation
- Empirical research
- Inventory control
- Consumer preferences
- Strategic planning
- Profitability
- Supply chain management
- Transfer pricing

Search 2 – Subject: Thesaurus Term

- Pricing
- Prices
- Marketing
- Retail industry
- Decision making
- Marketing strategy
- Electronic commerce
- Empirical research
- Strategic planning