FROM CUSTOMER DATA TO CUSTOMER'S DATA: REVERSE USE OF CUSTOMER DATA AS A TOOL FOR VALUE CO-CREATION

Jyväskylä University
School of Business and Economics

Master's Thesis

2021

Author: Ella Horttanainen
Subject: Marketing
Supervisor: Juha Munnukka

JYVÄSKYLÄN YLIOPISTO
UNIVERSITY OF JYVÄSKYLÄ

ABSTRACT

Author
Ella Horttanainen

Title
From customer data to customer’s data: Reverse use of customer data as a tool for value co-creation

Subject	Type of work
Marketing	Master’s thesis
Date	**Number of pages**
2021	58 + appendices

Customer data has long been viewed as a resource that mainly benefits the company that is collecting it. However, due to the increased popularity of service-based business models and ideas of value co-creation, the role of customer data has changed and the value created from customer data has shifted to focus more on customers themselves. As a result of these changes, new services have been developed that are giving data back to customers and creating value for them in the process.

The objective of this research is to investigate the impact of data-based value creation towards customer’s perceived value, attitudes and customer loyalty measures (payment intention and recommend intention) as well as the relationships between these concepts. The research was done in cooperation with Storytel, an audiobook and e-book streaming service operating in Finland. The empirical part of the research was conducted as a quantitative research, in which the data was collected via an internet survey. To investigate the research questions, two identical surveys were created and sent to a group that had been exposed to reverse use of customer data as well as a control group, in order to compare the two research groups with each other. The results of the two surveys were first combined and then analyzed by using SPSS and Smart PLS software.

The results of this research indicate that the reverse use of customer data has a direct positive effect on perceived value, payment intention and recommend intention. However, there were no significant results regarding its effect on the relationship between perceived value and the loyalty measures. The results also displayed significant positive relationships between perceived value and payment intention, recommend intention and attitude towards the service, as well as significant positive relationships between attitude, payment intention and recommend intention.

The findings can be used as an encouragement for companies to develop tools and services that utilize reverse use of customer data, since it has a strong direct influence on perceived value, which eventually also affects customer loyalty. More practical research questions regarding the effects of reverse use of customer data can be addressed in future research once the phenomenon gains more understanding.

Keywords
Customer data, Reverse use of customer data, Service-dominant logic, Value co-creation, Perceived value, Attitude towards a service, Payment intention, Recommend intention

Place of storage
Jyväskylä School of Business and Economics

TIIVISTELMÄ

Tekijä Ella Horttanainen	
Työn nimi Asiakasdatasta asiakkaan dataksi: Asiakasdatan käänteisen käytön vaikutukset arvon yhteisluonnin prosesseihin	
Oppiaine Markkinointi	Työn laji Pro gradu -tutkielma
Päivämäärä 2021	Sivumäärä 58 + liitteet

Asiakasdatan on perinteisesti nähty hyödyttävän pääasiassa niitä keräävää yritystä. Viime vuosikymmeninä suosiota kasvattaneiden palvelukeskeisten liiketoimintamallien sekä arvon yhteisluonnin ansiosta asiakasdatan rooli on kuitenkin muuttunut, ja dataa käytetään yhä enemmän myös asiakkaan hyväksi. Näiden muutosten seurauksena on kehitetty myös uusia palveluja, joiden avulla yritykset voivat jakaa dataa asiakkaiden kanssa ja näin osallistua asiakkaan arvonluontiprosesseihin.

Tämän tutkimuksen tavoitteena on selvittää asiakasdatan käänteisen käytön vaikutuksia asiakkaan kokemaan arvoon, asenteisiin ja asiakasuskollisuuden mittareihin (maksuaikomus ja suositteluaikomus) sekä näiden käsitteiden välisiin suhteisiin. Tutkimus tehtiin yhteistyössä Suomessa toimivan ääni- ja e-kirjojen suoratoistopalvelu Storytelin kanssa. Tutkimus toteutettiin kvantitatiivisena tutkimuksena, jossa aineistonkeruumenetelmänä hyödynnettiin internet-kyselyä. Tutkimusongelman selvittämiseksi sama kysely lähetettiin kahdelle asiakasryhmälle, joista vain toinen oli altistettu asiakasdatan käänteiselle käytölle. Kahdesta tutkimusryhmästä saadut tulokset yhdistettiin ensin yhdeksi aineistoksi ja analysoitiin sen jälkeen SPSS- ja Smart PLS -ohjelmistojen avulla.

Aineistosta saatujen tulosten mukaan asiakasdatan käänteisellä käytöllä on suora positiivinen vaikutus koettuun arvoon, maksuaikomukseen sekä suositteluaikomukseen. Ilmiön vaikutuksesta koetun arvon ja uskollisuuden mittareiden välisiin suhteisiin ei kuitenkaan saatu tilastollisesti merkitseviä tuloksia. Tulokset vahvistuvat myös koetun arvon positiivisen vaikutuksen maksuaikomukseen, suositteluaikomukseen ja asenteisiin palvelua kohtaan, sekä positiivisen vaikutussuhteen asenteiden, maksuaikomuksen ja suositteluaikomuksen välillä.

Tutkimustulosten pohjalta voidaan rohkaista yrityksiä kehittämään lisää asiakasdataa hyödyntäviä palveluja ja työkaluja, sillä tulosten mukaan asiakasdatan käänteisellä käytöllä on vahva suora vaikutus sekä koettuun arvoon, että välillisesti myös asiakasuskollisuuteen. Ilmiön ymmärrystä voidaan lisätä tulevissa tutkimuksissa, jolloin myös asiakasdatan käänteisen käytön vaikutuksia koskeviin käytännön kysymyksiin voidaan vastata paremmin.

Asiasanat
Asiakasdata, asiakasdatan käänteinen käyttö, palvelukeskeisyys, arvon yhteisluonti, koettu arvo, asenteet palvelua kohtaan, maksuaikomus, suositteluaikomus

Säilytyspaikka
Jyväskylän yliopiston kauppakorkeakoulu (JSBE)

LIST OF TABLES AND FIGURES

TABLES

FIGURES

CONTENTS

1 INTRODUCTION

Customer data has traditionally been considered as information that is collected and analyzed with the company's benefit in mind. According to Thaler (2011), the perspective in which companies view customer data is often "narrow and limited" and consists mainly of thoughts on how the company itself can utilize the data. In practice, customer data has been used as a source of information to guide the company's customer relationship management (CRM) practices related to tactics like cross-selling and finding the most profitable customer segments (Saarijärvi et al. 2016). It has also been used as evidence in decision-making processes related to future marketing strategies. Despite the recent developments in CRM where customer data has become an essential tool for tailoring customized promotional messages to also delight the customers themselves, the overall ability to benefit from customer data in the current CRM framework can be described as rather asymmetric and more tilted towards the company's side.

However, as an increasing number of companies are changing their processes to have a more service-based business model, the conventional way that companies view and use customer data has been challenged (Saarijärvi et al. 2016). Since the more traditional, company-centric view of data is based on the ability to sell more products, it no longer fits the company's new strategic goal of serving customers (Saarijärvi et al. 2013). The focus of creating the best services that delight customers has also played a part in the development of new technologies and processes in which customer data can be returned to the customer.

1.1 Previous literature and practical examples

Until recently, research around the utilization of customer data has mostly centered around existing, more firm-centric CRM practices (e.g., Nguyen & Mutum, 2012; Verhoef et al. 2010). Thus, the concept of reverse use of customer data is a relatively new area of research in the field of marketing since most of the research articles about the subject are published within the last decade. This statement can be supported by the fact that Marketing Science Institute mentioned the role of data in marketing practices as a growing area of interest in their article "Research

Priorities 2018-2020” (2018). One of the research questions specifically highlighted the ways in which data can be used as a tool for delighting customers.

In earlier research, this specific area of study has sparked special attention among Finnish researchers, since most relevant articles regarding the subject are published by Finnish authors. For example, researchers Hannu Saarijärvi and Hannu Kuusela have written several articles about the reverse use of customer data and data-based value creation. In one of their articles, the researchers state that by giving customers access to the data, the company can provide them with new tools and information that help customers create more value for themselves. This increases the company’s service orientation by broadening its ability to support customers in their value creation processes (Saarijärvi et al. 2014).

The key terms surrounding the phenomenon include customer data, value co-creation and service-dominant logic. As for the phenomenon itself, its novelty has lead to several different definitions being used simultaneously in existing literature; Saarijärvi et al. (2014) describe the concept with the term reverse use of customer data, whereas Lim, Kim, Kim, Heo, Kim and Maglio (2018) use the term data-based value creation in their article. In addition, the complete process of providing useful data for the customers and helping them create value-in use in their own activities is referred to as customer process management (CPM) in a framework presented by Lim et al. (2019). In this research, the terms reverse use of customer data and data-based value creation will both be used to describe the phenomenon.

So far, existing research around the topic has been focusing mainly on either describing the phenomenon through a case company or building a theoretical framework around relevant concepts. While these studies have made assumptions about benefits that follow the reverse use of customer data such as the increase of perceived value, clear evidence of these benefits has yet to be measured. This research seeks to provide such evidence along with insights for developing better relationships between the customer and the firm. In the future, similar insights will be increasingly important for businesses that want to leverage the full potential of the data they are collecting and creating extra value for their customers. The customer perspective of the phenomenon is also expected to gain more interest in future research as the increased attention towards the ownership of data and data privacy policies have become the new norm for all businesses in recent years.

Practical examples of reverse use of customer data include different services, apps and features where customers can for example browse their purchasing history and acquire more information about their spending habits related to a specific company or service. These kinds of additional services give the data back to the customer in a way that creates value and increases the level of loyalty between the customer and the firm. For example, at the end of every year the Swedish music streaming service Spotify offers their customers a visual recap of all the music the customer has been listening to in the previous year.

Some companies have even developed their services beyond entertainment value to also provide tips and recommendations based on the customer's purchasing history or usage habits. Usually, the purpose of giving recommendations is to make the customer's life better or easier by for example improving the customer's health, guiding the customer towards more economical behaviors, or helping the customer reach the full potential of using the product or service. These types of health-related services based on purchasing history are already being offered by two of the largest grocery store chains in Finland, Kesko and S Group. In addition, one of Finland's major financial companies, OP Financial Group, has developed a tool for their customers that allows them to keep track of their monthly expenses and make saving plans according to their spending habits. The tool is free and accessible to customers in the company's mobile application.

1.2 Research objectives

The purpose of this research is to shed light on the impact that data-based value creation in a form of a service has regarding the changes in customer's perceived value and customer loyalty. The following research questions are addressed to fulfil this purpose:

1. How does data-based value creation affect the customer's perceived value towards the service?

2. How does data-based value creation affect customer loyalty in the form of payment intention and recommend intention?

This research is conducted as a quantitative analysis in which the empirical research material is collected through an online survey. The empirical part of the study is made in collaboration with Storytel, an audiobook and e-book streaming service operating in Finland. The company had recently launched its first yearly summary feature, Storytel2020, that contained informative and entertaining insights of the customer's reading and listening history from the previous year. The summary feature can be seen as a good example of an additional service that is leveraging the reverse use of customer data, making Storytel a suitable case company for this research.

The participants for the survey are selected from a group of customers who have received a company-produced summary feature containing customer usage data from the past year. In the survey, the participants are asked to answer questions regarding their perceived value, attitudes towards the service and customer loyalty. The responses received from the survey are then analyzed by using the SPSS statistical analysis software as well as Smart PLS 3.0 software. Finally, the results are compared to the initial research hypotheses and the outcomes of the study are presented in the conclusion section of this research paper.

1.3 Research structure

This research paper consists of five chapters in total. In the introduction section, the topic and the academical context as well as the purpose of the research are briefly presented before uncovering the structure of the paper on more detail. After this, the theoretical background is introduced with the help of a few key terms and concepts as well as previous research written about the subject. The conceptual framework and hypotheses of this research will be uncovered in more detail at the end of the theoretical chapter. The research methods and data collection procedures used in the study are then explained, after which the implementation of the study and the results are presented in the results section. Finally, the last chapter summarizes the conclusions made from comparing the results of the study to the initial hypotheses and presents limitations as well as ideas for future research about this topic. The graphical presentation of the research structure can be seen in Figure 1.

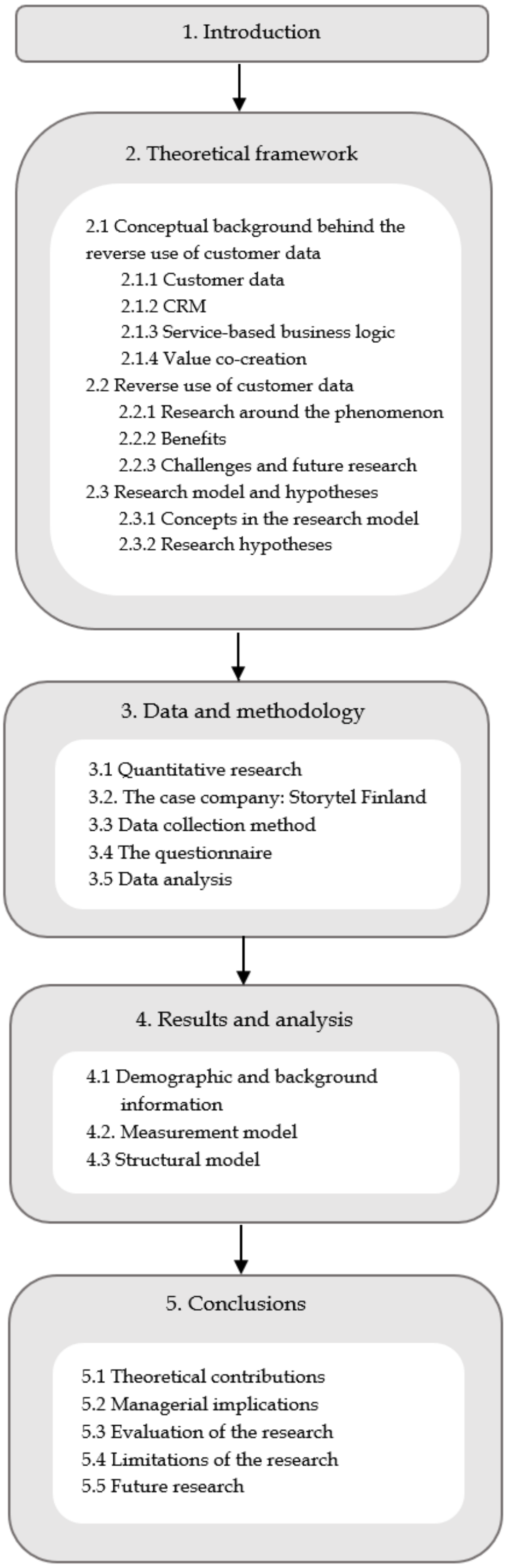

FIGURE 1 Research structure

2 THEORETICAL FRAMEWORK

2.1 Conceptual background behind the reverse use of customer data

This section will provide an overview about central concepts that act as a foundation for the discussion around the reverse use of customer data. First, the concept of customer data is introduced as the basis of the research phenomenon, after which other preceding concepts, CRM and service-based business logic, are defined and discussed in more detail. Lastly, the concept of value co-creation is introduced and explained with the help of findings from previous studies.

2.1.1 Customer data

According to Davenport and Prusak (1998), customer data can be described as "a set of discrete, objective facts about an event". In this research, customer data refers to the raw data that is being collected by the company from customers and the different activities they perform. The traditional view of customer data has revolved around receiving useful information about customers from the company's perspective. To this day, it is seen as an important asset for the company to gain competitive advantage by predicting customer behavior (e.g., Shankar & Winer, 2006; Homburg et al. 2009) and subsequently responding to market demand with the right offering (Saarijärvi et al. 2016).

There are several ways in which customer data can be used in the company's business operations. Companies can analyze data to design new services (Lim, Kim, Heo & Kim, 2018; Lim, Kim, Kim, Heo, Kim & Maglio, 2018), identify new potential markets and create more diverse value propositions inside these markets (Saarijärvi et al. 2014). In addition, communication of these value propositions can be customized to different customer segments, which are also generated with the help of customer data. Finally, data-based cross-selling and up-selling activities can be performed to sell more to existing customers and build lasting customer relationships (Payne & Frow, 2005). These operations help companies distinguish profitable customers from unprofitable ones (Peppers et al. 1999), eventually making their marketing efforts more cost-effective.

From the customer's point of view, the majority of benefits the customer receives from the utilization of customer data are indirect. For example, targeted and personalized marketing messages give customers more relevant content, whereas data-based category management helps companies curate their offering according to customers' needs (Saarijärvi et al. 2014). However, the ultimate objective of these activities is to serve the company in its efforts to increase sales and reduce marketing costs.

According to Grönroos (2008), efforts to support customer's value creation, the underlying goal in service-based business logic, are often disregarded since the existing methods for using customer data are widely product-centric. When customized promotions based on point-of-sale data create a positive effect on customers' purchasing processes while the overall benefit is still directed towards the retailer, the benefits received by the company and customer become unbalanced and the potential of using customer data for the customer's benefit is ignored (Saarijärvi et al. 2016). However, as the amount of recorded customer data experiences rapid growth, the importance of data-based services designed for customers themselves is expected to increase as well (Hoffman & Novak, 2018; Ng & Wakenshaw, 2017; Lim, Kim & Maglio, 2018; Lim et al. 2019).

The new role and purpose of customer data in today's marketing activities is to not only provide information for the company but to also be shared with customers, following the change of portraying customers as more of an active participant in company's processes (Saarijärvi et al. 2013). This new perspective has been reinforced by initiatives in both public and private sectors (Thaler, 2011). The reciprocal use of customer data is also important in terms of data acquisition since customers may be less likely to provide data if they receive no direct benefits from doing so (Boulding et al. 2005).

2.1.2 CRM

When discussing customer data and its role in customer's value creation processes, the concept of CRM (Customer Relationship Management) must be taken into account. Payne and Frow (2005) describe CRM as a holistic concept of managing customer relationships where the use of customer data has an important role.

The term CRM was initially used to describe the technical processes of collecting customer data and managing customer-firm relations (Boulding et al. 2005), but later evolved to also include the strategies, philosophies and technologies related to customer data and its management (Zablah et al. 2004). Gradually, CRM became the term for a more holistic approach of managing customer relationships in addition to customer data, as researchers started to discover different strategies and tactics of customer relationship management and compare them to each other (Saarijärvi et al. 2013). In marketing research and theory, CRM is closely related to relationship marketing and the idea that nurturing customer relationships is the foundation of the firm's marketing operations (Reinartz et al. 2004).

According to Lusch (2007), CRM was originally viewed as a tool for reciprocal value creation that benefits both the customer and the firm. Boulding et al. (2005) even declare that the fundamental purpose of CRM was more directed towards creating value for the customer instead of focusing on the company's objectives such as selling more products. In practice, CRM activities have received inspiration from mass customization (Pine, 1993) and one-to-one marketing concepts (Peppers & Rogers, 1993, 2004; Peppers et al. 1999) which are targeted towards customers but are designed to mainly benefit the company's value creation processes, resulting in CRM becoming a more company-oriented concept. (Saarijärvi et al. 2013). Even companies relying on service-based business models have largely ignored the wider potential of CRM as a tool to improve customer service and create value (Saarijärvi et al. 2014). Thus, the initial views of CRM have been overshadowed in practice by the thought of perceiving customers as passive recipients of marketing activities (Lusch, 2007) and the widely used CRM activities being relatively goods-oriented and focusing more on value-in exchange processes.

However, the current role of customer data in CRM systems is slowly changing as the CRM framework has "evolved through data dispersion, data organization and data ownership, towards data sharing" (Saarijärvi et al. 2013). The newest phase of this evolution is seen in companies' motivation to discover new ways to share data and create platforms where customers can themselves participate in the value-creation processes. This wider perspective still includes the more traditional CRM processes like segmentation and customization but also takes the customer's role into account (Saarijärvi et al. 2013.)

2.1.3 Service-based business logic

In the words of Vargo and Lusch (2004), the concept of service is defined as "the application of specialized competences (knowledge and skills), through deeds, processes, and performances for the benefit of another entity or the entity itself." In the context of this study, the term service is used to collectively depict the range of offerings a company provides for the customer.

The concept of service is closely tied to the company's value creation processes. According to Edvardsson et al. (2005), service can be seen as a perspective on value creation instead of a type of offering. The thought has been reinforced in several studies stating that customers consume everything as a service regardless of whether their subject of consumption is a physical product or an intangible service (Grönroos, 1978, 2008; Gummesson, 1995; Vargo & Lusch, 2004, 2008;

Grönroos & Ravald, 2011). An economist and Nobel Prize winner Gary Becker (1965) explained this with a notion that instead of the product or service itself, customers are more interested in the benefits and value creation opportunities of using the product/service in question.

The logic of service is described by Gummersson (1995) as a concept where all resources a company offers to customers contain potential value that can be utilized by the customer in a form of a service. In this logic, the customer is considered as the main creator of value since the service only creates value when used by the customer. Value-in-use, the term for value that is created when customers use the resources provided by the company, is an essential part of understanding service logic and challenges the more traditional view of value-in-exchange, where value is believed to be already embedded in the products manufactured by the company (Grönroos & Ravald, 2011).

The role of service provider in the customer's own value creation processes is one of the factors determining the concept of service logic (Normann & Ramirez, 1989). With the help of service logic, a service provider can extend its opportunities of influencing its customers compared to a more traditional business logic (Grönroos & Ravald, 2011). According to Grönroos (2006), service provider can adopt a service logic by actively engaging with customers during the production and consumption phases of the service. In a situation where the possibilities for such engaging interactions are remote, the service provider can also try and create interactions with additional services and platforms for reciprocal communication (Grönroos & Ravald, 2011). Examples of these platforms can include customer service channels, technological support, mobile applications and separate websites. Customer data -based value creation services can also be considered as additional platforms for customer-supplier interactions.

Grönroos and Ravald (2011) state that customer value creation takes place through two sub-processes. First, the supplier provides the customer with the necessary resources, after which these resources are used to create value in the customer's own processes. In service-dominant business logic, the roles of producers and consumers are blended together and are not as distinct as in a goods-dominant business logic. Value is created through co-creation efforts between the supplier, the customer and other stakeholders. The amount and quality of the value created is however always determined by the customer, in other words, the beneficiary of the value (Vargo et al. 2008.)

Following the increase of service orientation in business models, the role of customer data has also received more attention as companies have started to search for new ways to delight their customers. The potential value of customer data as a resource for the customer's value creation activities has been the focus of this refiguration process, providing a contrast to the previous role of customer data as one of the company's tools to sell more products (Saarijärvi et al. 2013). With the process of turning customer data into useful information for customers, companies are producing additional resources for value creation that can be extended to cover more than just the exchange of goods (Grönroos, 2011). Eventually, the goal of the service-based business logic is to change the role of the company from a passive contributor to an active supporter of customers' daily activities (Saarijärvi et al. 2014) and creating more ways to utilize customer data is a promising tool for trying to accomplish this goal.

2.1.4 Value co-creation

Customer value, defined as "the consumer's overall assessment of the utility of a product based on the perceptions of what is received and what is given" (Adams, 1963, 1965; Zeithaml, 1988), is at the heart of all marketing activities (Holbrook, 1994). This chapter deals with customer value from the perspective of co-creation, where the knowledge and skills of one party are used for the benefit of another (Vargo & Lusch, 2004).

From the more traditional point of view, the customer is viewed as the main creator of value whereas the supplier has the role of a value facilitator. The resources produced by the supplier are used as material for customers' value creation, thus making the supplier contribute to the process in an indirect way. However, when interacting with customers, the supplier is given an opportunity to become part of the value creation process and to increase the value the customer receives from the process (Grönroos & Ravald, 2011.) According to Gupta and Lehman (2005), value creation is eventually a two-sided process that produces value for both the customer and the supplier. While supporting customer's process of value creation is considered to be the main focus of any business engagement, the supplier should also benefit from the process and receive value to ensure the profitability of its business activities (Grönroos & Ravald, 2011).

The concept of customer process is closely related to value co-creation and is defined by Payne et al. (2008) in their research as "a series of activities performed by the customer to achieve a particular goal." While studying the concept, they discovered that the co-creation of value occurs during the constant interactions between processes run by both the customer and the supplier. These interactions are necessary since they create opportunities for value co-creation throughout the customer process and provide different strategic options for how and when the value is being created. The concept of interaction, described as a joint activity between two or more participants that have an impact on one another (Grönroos & Ravald, 2011), has also received attention in other studies related to service marketing (Grönroos, 1982; Lehtinen & Lehtinen, 1991; Grönroos, 2000; Gummesson, 2011).

In their study, Grönroos and Ravald (2011) examined the processes of value co-creation and the relationship between customer and supplier in the context of service-based business logic. The study described the value creation process with a model in which both the customer's and service provider's processes are divided into two parts; a part where there is an opportunity for mutual interaction and a part where such opportunities are non-existent. The model in question can be seen in Figure 2. According to the study, the possibility of the supplier becoming a co-creator of value becomes apparent during these mutual interactions where the supplier can access the customer's value creation process. For the supplier, opportunities for such interactions usually take place after the production phase of the service, whereas the customer is faced with these opportunities at the beginning of the value creation process where the link between the two processes is open and the resources provided by the supplier are used by the customer as a service. These findings can be used to further emphasize the importance of interactions between the customer's and service provider's processes.

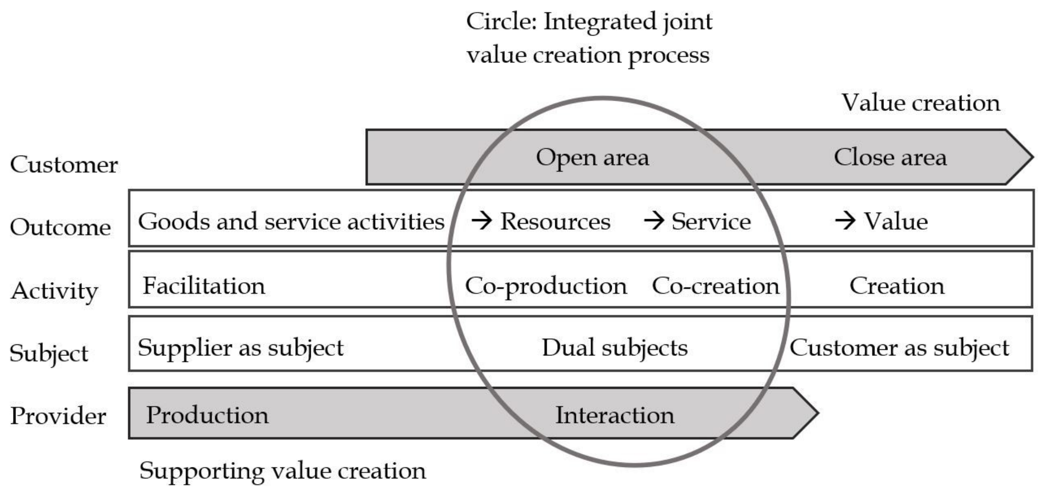

FIGURE 2 Value creation and co-creation in supplier-customer relationships (Grönroos & Ravald, 2011)

When creating services that support value co-creation, customer data and information that is developed from it is considered as one of the main resources (Vargo et al. 2008). Service providers can create value-in use during customer processes by collecting data from customers, developing the data into valuable information and presenting it to customers in a way that allows them to improve their own processes based on the information they are given. This combination of sharing information through interactions is the underlying method for value co-creation in services that focus on customer process management (Lim et al. 2019).

It can be concluded that in addition to service providers being the facilitators of value, they can also receive opportunities for value co-creation alongside customers during interactions within the customer's own processes (Grönroos & Ravald, 2011). The chances of value co-creation during these interactions can also be enhanced with customer data that are given back to the customer as useful information. This phenomenon of customer data -based value creation will be discussed in more detail in the next section.

2.2 Reverse use of customer data

In their article, Saarijärvi et al. (2014) effectively summarize the theoretical background of this study: Companies have traditionally tried to gain a competitive advantage through customer data by using the data primarily as a resource in product development and in identifying the most profitable customers. Later this product-centric perspective has shifted to a more customer-oriented mindset and efforts have been made to develop value production for the benefit of both the company and the customer. The role of customer data in this reciprocal value creation process has also been reviewed, studies stating that the external use of customer data can act as a facilitator towards the company's new objective of supporting customers' value creation. However, since the phenomenon has not yet been explored much in academic literature, it still lacks a strong theoretical foundation and therefore needs to be approached with a level of alertness (Saarijärvi et al. 2014).

As a result of the Big Data movement, more and more valuable customer data are being produced as a by-product of customers' day-to-day operations (Mayer-Schönberger & Cukier, 2013). This proliferation of data has created a good breeding ground for new types of services where customer-generated data is at the heart of value creation. Data can be defined as the raw material from which the most useful parts for a specific purpose are filtered using data analysis. These parts are then combined to create information for customers, who use it as a resource in their value creation (Lim et al. 2019). With the right kind of technology and management of information, customer data can be used to produce information that customers can benefit from. However, the opportunities of transforming customer data into customer information have yet to be widely recognized by companies (Saarijärvi et al. 2014).

2.2.1 Research around the phenomenon

Due to its novelty as a research topic, there is no one generally accepted term for describing the phenomenon of using customer data for customer's value creation. One of the terms used in this context is "reverse use of customer data" which has been introduced in a few articles regarding the phenomenon (Saarijärvi et al. 2014; Saarijärvi et al. 2016). Saarijärvi et al. (2016) define reverse use of customer data as a process where companies transform customer data into meaningful information for the customers. This process requires both a redefinition of the role of customer data to extend also towards the benefit of the customer, as well as the construction of systems that help transform the data into information. In the words of Saarijärvi et al. (2014), reverse use of customer data "counteracts the traditional logic of customer data usage". Reverse use of customer data provides additional resources especially for companies that rely on service-based business logic instead of a more product-centered approach.

"Customer relationship management: The evolving role of customer data" by Saarijärvi et al. (2013) is one of the first articles in marketing research that closely examines the possibilities of using customer data as a resource for customers' value creation and portrays a more holistic picture of the new role of customer data within the CRM framework. In their study, the authors found that in the context of their empirical research case, a data-based service provided by a major Finnish food retailer offering nutritional information for its loyalty card holders, the reconfigured role of customer data could be described in four themes: customer loyalty, firm differentiation, firm values and firm image.

For customer loyalty, the attractiveness and relevance of the information received by customers were the factors that had the greatest impact on loyalty towards the company. Customers who felt they received useful nutritional information about their grocery shopping were also more willing to concentrate their purchases more on the same retailer. Some customers even changed their purchasing habits entirely and switched their preferred retailer after using the service. What should be noted in the results, however, is that the service was originally targeted at the company's existing customers who also held the company's loyalty card, making the level of customer loyalty fairly high to begin with.

The second theme, firm differentiation, addressed the phenomenon where reconfigured customer data helped the retailer to differentiate itself from competitors as well as to attract new customers. Providing customers with useful information in addition to their main offering, the retailer also strengthened its own image as a service company in the eyes of customers.

For firm values, the retailer was able to highlight its strategic goals towards customer orientation by showing customers one way of engaging them in reciprocal value creation on a more practical level. Giving customers access to their own data increased customer's perceptions of two of the company's core values, corporate responsibility and exceeding customer expectations.

The reconfiguration of customer data was also found to have a positive impact on the firm image. The results stated that because of the service, customers perceived the retailer as an innovator and a fair partner for their value creation. The fact that customers received benefits in return for using their loyalty card also had an impact on their perceptions on the retailer's image. The four themes found in the study all support the company's value creation in different ways and at different stages, on both operational and strategic level.

Later, Saarijärvi et al. (2014) investigated the phenomenon further by including a new perspective; what kind of implications can be derived from reverse use of customer data for service-based business models. Following the characteristics of service-dominant logic and value co-creation (see parts 2.1.3 and 2.1.4), reverse use of customer data is seen as a tool for supporting customer's value-in-use through additional services and increased opportunities for mutual interaction, whereas the more traditional use of customer data is seen to mainly cater to the company's sphere of value creation. The visual representation of this perspective can be seen in Figure 3.

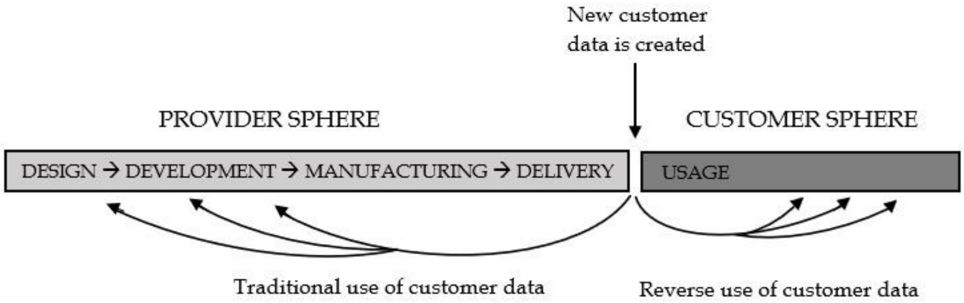

FIGURE 3 Using customer data for customer value creation (Saarijärvi et al. 2014)

To better understand and analyze the effects of reverse use of customer data on service-based business models, the study applied a framework of business model parameters presented by Chesbrough (2007; Kindström, 2010), consisting of five slightly modified parameters; value proposition, revenue mechanisms, value chain and value network, competitive strategy and target market. The first implication was that the delivery of company's value proposition can be supported and expanded by giving customers more resources through reverse use of customer data. Giving data to the customers can also generate new revenue mechanisms by attracting customers to make the initial purchase, encouraging customers to spend more while giving them personalized information about their consumption habits or by developing services that can be sold to customers separately.

When it comes to value chain and value network, reverse use of customer data can be a process that demands expertise from outside the company's scope. Therefore, companies need to be ready to cooperate with external stakeholders and acquire the necessary resources to create such services. Since the potential of reverse use of customer data has yet to be fully taken advantage of among businesses, it also contains opportunities for competitive strategies, which will be covered in more detail later in this chapter. Lastly, the reconfiguration of customer data can be used to discover new customer segments and find new target markets. For example, offering environmentally conscious consumers information that is directly linked to their interests, such as tips on how to reduce the carbon footprint of their grocery purchases, can be an effective way to turn potential customers to actual customers.

In addition to the term reverse use of customer data, another term, data-based value creation, has been used to describe the phenomenon. Lim, Kim, Kim, Heo, Kim and Maglio (2018) studied the topic in the context of information-intensive services (IIS), services in which information interactions between the customer and the provider are the main source of value creation instead of physical or interpersonal interactions (Karmarkar & Apte, 2007; Lim & Kim, 2014). In their research, the process of data-based value creation in IISs is defined in the following manner. First, customers seek to achieve their own goals by interacting with the company in specific processes (Bettencourt & Ulwick, 2008), to which the companies respond by offering value propositions such as IISs to customers. This creates moments of interaction where customer-related data is collected through service operations (Lim et al. 2012). The data is then analyzed and transformed into useful information by the company (George et al. 2014), after which the information is delivered to customers who use it in their value creation processes (Saarijärvi et al. 2014). The researchers state that in today's data-filled business environment, understanding this process is vital for companies that seek to improve the value creation of their services with customer data.

Lastly, Lim et al. (2019) summarized the whole process of customers using the data collected by the company to improve their own performance by introducing the term customer process management (CPM). With this broader and more customer-centered perspective of data-based value creation, companies are encouraged to look beyond individual services and to create comprehensive solutions for every step of the customer's process. This can also act as a liberating factor for developing new, more innovative solutions for customers.

Data that is being used in CPM can be obtained either directly from customers or from objects used by customers. Customers can themselves produce data related to health, behavior or purchase history etc. whereas the objects they interact with can collect data such as the condition of the product or event log. Data is recorded and collected during customer's processes and then produced into information in the company's own processes. The content of the information that is received from the data can either relate to the current state of the data source such as customer's health, or to the process that the data source is experiencing such as the fuel intake during a commute. With the provided information, customers can monitor their performance on certain tasks such as driving a car or exercising and then change their behavior according to the goal they want to achieve. The goals may for example include increased efficiency, speed or a more sustainable way of performing the task. Value-in-use is eventually created when customers succeed in completing these processes and reaching their desired goals (Lim et al. 2019.)

2.2.2 Benefits

The implementation of reverse use of customer data contains several benefits. For example, as a by-product of the phenomenon, new revenue models can be created either by adding reverse use of customer data to existing services or by developing new service models. This can eventually develop into a competitive advantage that is more difficult to emulate since the data produced by the company's individual customers is always unique. Information that is relevant, interesting and tailored for each customer based on the data they have created also acts as a great tool for a pull marketing strategy that aims to build lasting relationships between the company and its customers (Saarijärvi et al. 2014.)

The underlying factor behind reverse use of customer data creating competitive advantage is increased customer loyalty. Researchers Saarijärvi et al. (2016) found that customers are more likely to stay loyal to a company when the company is providing them with useful information that is beneficial for their well-being. This is based on the logic of reverse use of customer data where the accuracy of the information obtained from the data increases as the customer concentrates their purchases towards one company. With more accurate information, customers are also better able to improve their well-being and receive greater value from their interaction with the company. The positive impact of reverse use of customer data is even greater when combined with a customer loyalty program that already offers benefits to its members based on purchasing volume (Saarijärvi et al. 2016.) The interactive aspect of sharing information based on customer data can also create an emotional choice factor that further increases the formation of competitive advantage through higher affective switching costs (Meyer-Waarden, 2007).

Lastly, reverse use of customer data can help to dispel customers' doubts about CRM practices by avoiding activities known as "the dark side of CRM" (Boulding et al. 2005; Humby et al. 2004; Ngai, 2005). According to Frow et al. (2011), some of the doubts and fears that customers experience related to sharing their personal data include misuse of information, invasion of privacy and efforts to use customer data to strengthen customer lock-in strategies. Sharing the data with customers can increase the transparency of the CRM practices by showing what kind of data is being collected and how it can be used for the customer's benefit.

2.2.3 Challenges and future research

In addition to the benefits, there are several challenges associated with reverse use of customer data. For example, companies' willingness and motivation to share customer data may be weak or the company's ability to produce useful and interesting information from the data may be limited (Saarijärvi et al. 2013). Challenges may also arise in contrary activities where companies focus only on customer's value creation and use an excessive number of resources to create additional value from customer data (Gupta & Lehman, 2005). As a result, the overall profitability of utilizing reverse use of customer data decreases, creating a service paradox where investing in new value creation services fails to increase revenues gained from them (Gebauer et al. 2005). Conducting empirical research about the topic and gathering more information about the different reasons behind these challenges plays an important role in understanding the phenomenon.

When dealing with customer data, concerns about data privacy and correct data management are constantly present. According to Menon (2019), new regulations such as GDPR have forced companies to make changes to their marketing activities, specifically those based on customer data, in order to comply with the requirements. The standard for dealing with customer data is now higher and the process of collecting, processing and deleting the information needs to be more transparent. Due to the regulations, some companies may have even transformed their way of collecting and processing customer data completely. While these changes are largely positive and necessary for both parties, the wide-ranging use of customer data in business processes requires careful observance of strict privacy legislations, for which not all companies have enough resources and expertise.

In order to obtain sufficient customer data, customers must be willing to share their own personal data with the company. According to Schoenbachler and Gordon (2002), the proliferation of customer data collection and the increase in the amount of data collected by each company have, however, created privacy concerns among consumers. If the risk of misusing customer information is perceived as high by the customer, their willingness to engage in activities where customer data is being used might be lower. Establishing trust with customers by having more transparent data management processes and avoiding the previously discussed dark side of CRM can increase customer's willingness to share information with the company (Leppäniemi et al. 2017).

For future research, a further investigation towards the customer's perspective on reverse use of customer data would provide an interesting research topic. For example, questions on how consumers feel about companies utilizing their data and how likely they are to give more data to receive better service are topics that need to be covered to create a wider picture about the phenomenon (Saarijärvi et al. 2014). As for the more extensively covered business perspective, new research could focus on investigating new business models that can be created through reverse use of customer data (Saarijärvi et al. 2016).

2.3 Research model and hypotheses

2.3.1 Concepts in the research model

The concept of *perceived value* is described as the consumer's perception of the benefit of a product or a service that is received in comparison to its expenses (Chu & Lu, 2007; Kim et al. 2007). Following this definition, the perception of value can be reinforced by either having the product or the service contain more benefits or by reducing the expenses related to the purchase and use of said product/service (Lovelock & Wirtz, 2007). This study focuses on the former by observing on the additional benefits created for customers with reverse use of customer data.

According to previous studies about online services, perceived value has repeatedly been named one of the most significant factors to influence consumers (Kim et al. 2007; Chu & Lu, 2007; Lu & Lin, 2012; Lin et al. 2012) and especially their purchase behavior and willingness to pay for a service (Hsiao & Chen, 2017). Comparing the perceived value of a service to its costs is an important part of a customer's service evaluation process also among streaming services (Almquist et al. 2016), an industry in which the case company of this research is operating in.

Attitude can be described as a positive feeling that the customer has towards something (Hsiao & Chen, 2017), in this context a service that engages in data-based value creation activities. Attitude has been found to have a strong positive impact on customers' behavioral intentions (Park & Chen, 2007; Hsiao, 2013), for example the intention to purchase based on attitude towards online purchasing (Van der Heijden et al. 2003). In a study by Prendergast et al. (2010), customer's attitude towards an online forum was also found to be a powerful predictor of purchase intention.

Customer loyalty is an important part of company's profitability since it measures the customer's level of engagement and commitment to the company's offering, such as the company brand, products, services and other activities (Uncles et al. 2003). Loyalty can be viewed as either attitudinal loyalty where a customer is considered loyal based on their positive attitudes towards the company, or behavioral loyalty, where customers express their loyalty by continuing to buy from the company and to use their products or services (Peppers & Rogers, 2004). Loyalty can also be indicated through secondary behavior such as positive word-of-mouth and recommendations (Jones & Sasser, 1995; Uncles et al. 2003; Aksoy, 2013).

Due to the impact customer loyalty has on profitability, companies need to constantly measure and manage it (Reichheld, 2004). Businesses measure customer loyalty with several different metrics such as repurchase intention (Reichheld & Sasser, 1990) and recommend intention (Keiningham et al. 2011). *Repurchase intention* can be described as the probability of the customer engaging in future repurchase behavior (Seiders et al. 2005), or the customer's willingness to keep buying the product or service from the same provider (Hamza, 2013). The effect of repurchase intention to a company's performance has found to be significant, therefore making it one of the most critical measurements for the company's management as well as for academic researchers (Aksoy et al. 2012). As for *recommend intention*, the term is described as the probability of a customer recommending the company and saying positive things about the company to other people (Zeithaml et al. 1996; Leppäniemi et al. 2017).

2.3.2 Research hypotheses

After reviewing the theoretical framework surrounding the phenomenon, it can be concluded that while reverse use of customer data has been the main topic in several studies, there is little empirical evidence of its measured impact on customer value, attitudes and loyalty. The aim of this study is to fill this gap in the existing literature and provide evidence of the impact that reverse use of customer data has on customers. The results of the study can be used to demonstrate the potential benefits of using customer data as a tool for value co-creation, which in turn provides new insights for the development of reciprocally beneficial customer relationships (Saarijärvi et al. 2014). Furthermore, when the findings of the reverse use of customer data are combined with discussion around widely used performance measures, service providers can be more motivated to find new ways to delight customers by using customer data (Saarijärvi et al. 2016).

The positive relationship between perceived value and customer loyalty has been supported in several studies (Brodie, Whittome & Brush, 2009; Grosso & Castaldo, 2015; Sirdeshmukh, Singh & Sabol, 2002; Yang & Peterson, 2004**).** In previous literature, the concept of attitudinal loyalty has been viewed both as a broader term including the measures repurchase intention and recommend intention (see e.g., Zeithaml et al. 1996) as well as a combination in which these two measures are considered as separate constructs. However, based on previous studies (De Matos & Rossi, 2008; Watson et al. 2015), the unidimensional construct of loyalty should be avoided and the preferred method for investigating the phenomenon would be to use repurchase intention and recommend intention as separate measures. Hence, this study will measure customer loyalty by examining these two constructs and then combining the results.

According to prior studies, repurchase intention is positively influenced by customer perceived value (Baker et al. 2002; Grewal, Monroe & Krishnan, 1998; Zeithaml, 1988). For this study, repurchase intention is replaced with the term payment intention. This is because the empirical part of the study examines a subscription service where payments are made regularly and without a separate purchase decision for each payment. In their study, Hsiao and Chen (2017) investigated the factors affecting the payment intention of an e-book subscription service and found that along with positive attitude towards the service, perceived value had a strong positive impact on payment intention. In addition, perceived value was also mentioned as a critical component in other studies regarding the motivational factors behind the willingness to pay for digital products and services (Lu & Hsiao, 2010; Park & Chen, 2007). Studies have also shown a positive relationship between perceived value and recommend intention (Gruen et al. 2006; Hartline & Jones, 1996; McKee et al. 2006). Thus, the following hypotheses are proposed:

H1: Perceived value has a positive effect on payment intention.

H2: Perceived value has a positive effect on recommend intention.

In addition to having a strong influence on customer loyalty factors, perceived value has also been found to have a positive relationship with attitudes toward the service (Hsiao & Chen, 2017; Lin, 2007; Kim & Forsythe, 2008). Hence, the following hypothesis is proposed:

H3: Perceived value has a positive effect on attitude towards the service.

As mentioned before, attitude towards the service has also been confirmed to have a strong positive influence on payment intention, which makes it the second major antecedent of customer loyalty along with perceived value (Hsiao & Chen, 2017). The predictive qualities of attitude towards purchase intentions in online environment were specially demonstrated by Prendergast et al. (2010). Since recommend intention is considered as the second construct measuring customer loyalty besides payment intention, this research predicts that attitude will also have a positive impact on recommend intention. The hypotheses regarding attitude towards the service are the following:

H4: Attitude towards the service has a positive effect on payment intention.
H5: Attitude towards the service has a positive effect on recommend intention.

Reverse use of customer data has a supporting role in delivering the company's value proposition to customers. With the available information, the company gives customers more resources for their own value creation, which in turn helps the company meet their expectations (Chesbrough, 2007). The value that is being created during this process is also more diverse and profound (Saarijärvi et al. 2014) and can create functional and economic benefits (Rintamäki et al. 2007), eventually broadening the company's value proposition opportunities. The value-creation potential of giving the data back to the customers has even been pointed out by behavioral economists (Thaler & Tucker, 2013).

As mentioned previously while covering the findings of Saarijärvi et al. (2013), customers are likely to be more loyal to the company when the process of reverse use of customer data provides them with relevant and interesting information. The impact is further amplified when the loyalty to purchase from one supplier is directly linked to the quality and accuracy of the information, such as in health-related recommendations that are based on customer's purchase data. This creates a win-win situation where higher loyalty equals better information and hence, more value for the customer (Saarijärvi et al. 2014).

In the following hypotheses, data-based value creation acts as a moderator to earlier hypotheses H1 and H2. The graphic representation of this dynamic can be seen in Figure 4.

H6: Data-based value creation strengthens the positive effect of perceived value towards payment intention.
H7: Data-based value creation strengthens the positive effect of perceived value towards recommend intention.

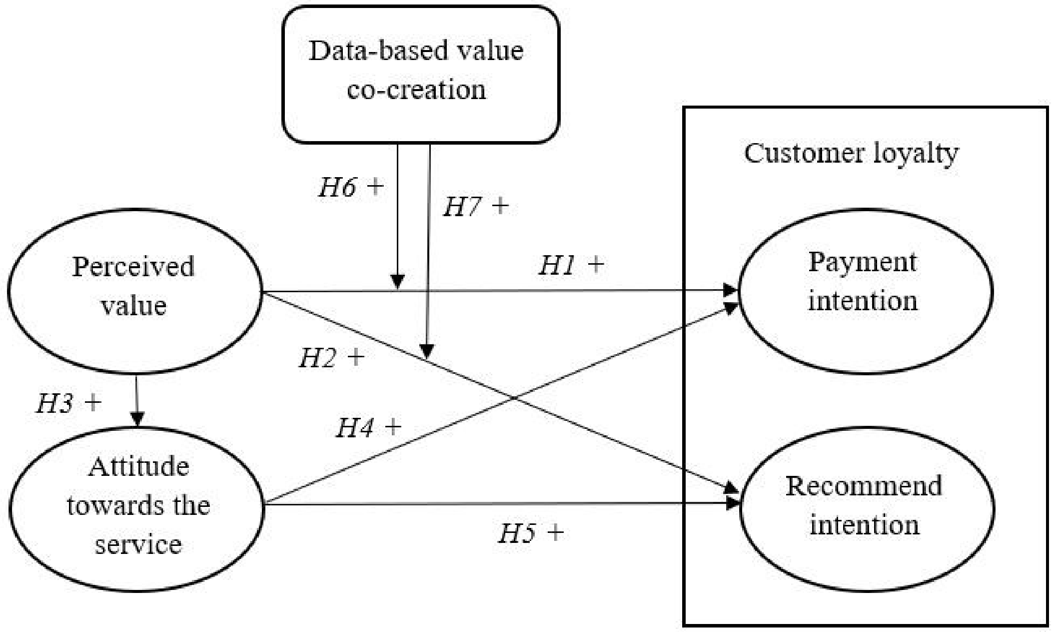

FIGURE 4 Research model

3 DATA AND METHODOLOGY

3.1 Quantitative research

This research was conducted as a quantitative study due to the explanatory nature of the research model. Quantitative research methods are used to explain, describe, compare or predict certain events by using measures to confirm or reject previously issued hypotheses. The qualities of quantitative research include structured information, the presentation of information in a numerical form and the objectivity of the results. In explanatory research, the aim of the study is to reveal the causes behind a certain phenomenon and investigate the correlation and possible causalities between the research objectives. (Vilkka, 2007.)

The purpose of this research is to measure the impact of data-based value creation on customer's attitudes and loyalty through perceived value, thus explaining the relationships and correlation between these concepts. Using quantitative measures makes it possible to set more precise estimates on the relationships between the research objectives (Bell et al. 2018). The choice for using quantitative methods is also justified in previous marketing literature as topics like customer perceptions and behaviour have traditionally been studied by using quantitative methods such as surveys to collect data.

3.2 The case company: Storytel Finland

The empirical part of the research was conducted in collaboration with Storytel, one of the world's leading audiobook and e-book streaming services that operates in 20 markets around the globe, including Finland. The research was done in collaboration with Storytel Finland.

The company offers its customers a subscription-based service that is used via an app on iOS and Android mobile devices. By paying a monthly fee for an ongoing subscription, the customer has access to over 300 000 items including audiobooks, e-books, podcasts and articles. The Finnish Storytel offers content in six languages and has several different subscription alternatives ranging from limited to unlimited access as well as family subscriptions.

In December 2020, Storytel published a yearly summary feature called Storytel2020 for the first time in its history. The summary available for Finnish customers contained 10 slides of information about their streaming habits such as total listening time and the number of books the customers had finished during that year. The summary also consisted of more entertaining information such as the height of an animal compared to the stack of books the customer had finished, the number of finished books compared with other users in the same market, longest reading/listening streak as well as the customer's most popular author and narrator.

The last slide of the feature was a summary screen specifically made for sharing on social media via screenshot. The purpose of the summary was to increase reciprocal interaction between the company and its customers by creating shareable content for social media channels, gradually leading towards higher levels of customer loyalty and exposure among consumers. At the time of this research, there were no other yearly summary features made by other service providers operating in Finland, which made it possible to also seek competitive advantage by publishing the feature.

The streaming data was collected from January 1st to November 30th, 2020, and the summary was accessible for customers from December 2020 until February 2021 via a separate website where the customers could log in with their account. The release of the summary was communicated to the customers via email and a notification inside the Storytel app. The summary was available for customers who had started to use the service before November 1st, 2020, and who had streamed at least 30 hours' worth of content between January 1st and November 30th, 2020. If the customer had been subscribed to the service for less than 3 months, the requirement for total streaming time was 10 hours. These requirements were put into place in order to have enough data for a meaningful summary feature for each customer.

3.3 Data collection method

The empirical data was collected via an online survey. A survey is an example of a structured data collection method where data is collected to answer specific research questions (Bell et al. 2018). Since the research questions in this study explore the relationships between well-known behavioural and attitudinal concepts that have been validated in previous research, this data collection method was considered to be the most suitable and effective option. Self-administered surveys such as online surveys where the respondents answer the survey on their own are also an efficient way to collect data from large groups of individuals and the results can be generalized to apply to a large population (Nardi, 2018). In earlier literature, survey as a data collection method has been used in several studies about customer perceptions towards online services (Hsiao & Chen, 2017; Kim et al. 2007; Lu & Lin, 2012).

During the data collection process, an identical questionnaire was sent to two different customer groups. The first group was the main research group and consisted of active customers who had opened the Storytel2020 yearly summary. The second group was the control group that contained customers who had received the summary but had not opened it. To increase the comparability of these two groups, the customers chosen for the control group had to have at least 15 hours of listening time during the last 30 days. The customers in both groups also had active subscriptions and an existing marketing permission. Since the two versions of the survey were identical, the only variable between the two groups would be whether the customers had opened the summary feature or not.

Before the release, the survey was tested by 6 respondents and modified according to their feedback. For example, some questions were changed to be easier to understand while trying to maintain the form of the original questions. After modifying the questions, a link to the survey was sent to each customer segment through email along with a cover letter on February 10th, 2021. The letter contained a brief introduction to the survey, addressed the privacy measures regarding the survey and gave a notion that the customers would have until the 18th of February 2021 to answer the survey. According to the respondents who had tested the survey, the answering time was estimated to be approximately 5-10 minutes.

3.4 The questionnaire

The respondents were first asked general questions about their reading habits in order to acquire relevant background information and to create a clear context around the responses. For example, the respondents were asked to evaluate how many books they usually read or listen to in one month, how long they had been using online e-book and audiobook subscription services and how long they had been using the service provided by the case company. According to earlier research, the length of the relationship in particular is considered a critical determinant of customer loyalty (Wang & Wu, 2012). At the end of the survey, the respondents were also asked to state their gender, age, the size of their household and their current occupation. These questions were asked to determine the demographic background of the respondents and to further create a context for the research results. In previous studies, demographic factors such as gender and age were also found to have a significant effect on the relationships between customer loyalty and relationship marketing (Alrubaiee & Al-Nazer, 2010) as well as the link between commitment and attitudinal and behavioural loyalty (Thaichon et al. 2016).

The constructs of the study were taken from the research model. Each of the constructs were measured by utilizing existing scales from previous studies, thus ensuring that the scales were already tested and validated. The complete survey consisted of 19 questions/statements and can be found in Appendix 1.

Statements for customer perceived value were adapted from a study by Kim et al. (2007). The study contained the following four statements: "Compared to the fee I need to pay, the use of the service offers value for my money", "Compared to the effort I need to put in, the use of the service is beneficial to me", "Compared to the time I need to spend, the use of the service is worthwhile to me", "Overall, the use of the service delivers good value to me".

Attitude towards the service was measured by combining statements from two previous studies (Hsiao & Chen, 2017; Childers et al. 2001) that both examined the attitudes and behavioral intentions of consumers using online services. The final scale contained four items in which the respondents were asked to evaluate on a scale of 1 to 7 how wise, beneficial and rewarding it was to use the service and how much they liked to use the service.

Payment intention was measured by adapting two statements from a study by Hsiao (2011). In both statements, the respondents were asked to consider whether they would regularly pay for the service in the future. For recommend intention, one of the measures used was NPS, as respondents were asked to evaluate how likely they would recommend the service to a friend or a colleague. WOM developed by Reichheld (2004) and Zeithaml et al. (1996) was also used to measure recommend intention by asking the respondents how likely they would tell positive things about the service. The list containing all research measures can be seen in Table 1.

All questions regarding the research objectives except recommend intention were measured by using a 7-point Likert scale where option 1 = completely disagree and option 7 = completely agree. For recommend intention, both questions regarding NPS and WOM were measured by using a 7-point Likert scale with option ranging from 1 = not at all likely to 7 = very likely.

TABLE 1 Research measures

Measure	Number of constructs	Source
Perceived value	4	Kim et al. (2007)
Attitudes	4	Hsiao and Chen (2017); Childers et al. (2001)
Payment intention	2	Hsiao (2011)
Recommend intention	2	WOM by Reichheld (2004) and Zeithaml et al. (1996), NPS

3.5 Data analysis

After the survey was closed from the public, the responses were uploaded from Google Forms to IBM SPSS Statistical Software to analyse the data. Out of 6100 recipients, the total of 676 customers answered the survey (research group = 391, control group = 285). Therefore, the response rate of the survey was 11%. Since all the questions in the survey were marked as mandatory, there was no need to check the data for missing values.

With SPSS, the data from two research groups was first combined into one dataset and the responses from the two groups were distinguished from one another by adding a new dummy variable with the values 1 = had opened the summary and 2 = had not opened the summary. The data was then prepared and descriptive qualities and frequencies of questions related to demographic and background information were analysed in order to gain more context for the results. Later, a T-test was also used to compare means between the responses of the two research groups that measured perceived value, payment intention and recommend intention.

For the confirmatory factor analysis and testing of the research hypotheses, partial least squares structural equation modelling (PLS SEM) was applied with Smart PLS 3.0 statistical software due to its ability to cover more complex and diverse relationships (Hair et al. 2016). In structural equation modelling, factor analysis and path analysis are combined into one comprehensive methodology that consists of two parts: the measurement model and the structural model (Kaplan, 2008). The measurement model portrays the relationships between constructs and the structural model is used to measure the significance of these relationships (Hair et al. 2016).

In addition to measuring correlations between the constructs by using combined data, multigroup analysis (Sarstedt et al. 2011) was conducted to test whether there were significant differences between the two research groups (Hair et al. 2016). Before the analysis, a moderating effect was applied to the structural model as a differentiating factor between the two groups. In multigroup analysis, the same research model is being tested on different samples of respondents and the results are compared to each other to reveal statistically significant differences between the individual samples. (Hair et al. 2016).

4 RESULTS AND ANALYSIS

The following chapter contains the results of this research. First, demographic and background information are introduced to understand the context of the results. Then, a measurement model is applied to investigate the validity of the measures used in the empirical part of the research before presenting the results regarding the research model and hypotheses with a structural model.

4.1 Demographic and background information

Demographic information for both research groups as well as combined data is presented in Table 2. Out of all respondents, the majority (79.6%, N=538) were female and 18.9% (N=128) were male. Only 1.5% of the respondents (N=10) chose the option "other or prefers not to say". The largest age group among the respondents was 40-49 years (26.8%, N=181), followed by 30-39 years (23.1%, N=156) and 50-59 years (19.7, N=133). Respondents under 20 years or over 70 years composed only 7.1% of the total responses. Based on these results, the majority of the respondents can be assumed to be middle-aged and women.

Almost 40% of the respondents stated that they were living in a household of 2 people (39.9%, N=270) and the second largest group were respondents living in a 1-person household (19.5%, N=132). For occupation, vast majority of respondents chose the option "Employed, full time or fixed term" (61.2%, N=414). The second largest group (17.9%, N=121) chose the option "Retired". In total, only about 12% of the respondents identified as students, part-time employees or unemployed, groups that are traditionally viewed as people with lower income.

The respondents of this study were not asked to state their yearly income. However, based on the results for household size and occupation, it can be assumed that the majority of respondents have sufficient income in order to continue paying for the subscription service if they consider the service to be valuable for them.

TABLE 2 Demographic information

	GROUP 1 (SUMMARY OPENED)		GROUP 2 (SUMMARY NOT OPENED)		COMBINED DATA	
	N	**%**	**N**	**%**	**N**	**%**
Group	391	57.8	285	42.2	676	100
Gender						
Male	67	17.1	61	21.4	128	18.9
Female	317	81.1	221	77.5	538	79.6
Other or prefers not to say	7	1.8	3	1.1	10	1.5
Age						
Under 20 years	3	0.8	3	1.1	6	0.9
20-29	41	10.5	15	5.3	56	8.3
30-39	104	26.6	52	18.2	156	23.1
40-49	108	27.6	73	25.6	181	26.8
50-59	76	19.4	57	20.0	133	19.7
60-70	40	10.2	62	21.8	102	15.1
Over 70 years	19	4.9	23	8.1	42	6.2
Household size						
1	72	18.4	60	21.1	132	19.5
2	149	38.1	121	42.5	270	39.9
3	65	16.6	40	14.0	105	15.5
4	76	19.4	40	14.0	116	17.2
5	22	5.6	17	6.0	39	5.8
More than 5	7	1.8	7	2.5	14	2.1
Occupation						
Student	18	4.6	15	5.3	33	4.9
Employed, full time or fixed term	258	66.0	156	54.7	414	61.2
Employed, part-time	15	3.8	6	2.1	21	3.1
Entrepreneur	35	9.0	25	8.8	60	8.9
Retired	46	11.8	75	26.3	121	17.9
Unemployed	19	4.9	8	2.8	27	4.0

All answers for questions concerning background information are presented in Table 3. The responses stated that 45.6% of the respondents (N=308) read approximately 3-5 books a month and 29.4% read more than 5 books. In conclusion, 75% of the respondents stated that on average, they read at least 3 books every month.

Over 60% of the respondents stated to have used e-book and audiobook streaming services for over 12 months (62.9%, N=425). Regarding the use of Storytel in particular, 43.6% (N=295) of the respondents had been using the service for over 12 months and 27.8% (N=188) for 6-12 months.

Based on the responses for these background questions, it can be assumed that the majority of respondents are active users of e-book and audiobook streaming services, have used them for a longer period of time and are also familiar with using Storytel. These results were expected since the recipients of the survey were chosen from customers with active subscription and more than 15 hours of listening time in the last 30 days.

TABLE 3 Background information

	GROUP 1 (SUMMARY OPENED)		GROUP 2 (SUMMARY NOT OPENED)		COMBINED DATA	
	N	%	N	%	N	%
Books per month						
Less than 1 book	5	1.3	3	1.1	8	1.2
1-2 books	94	24.0	67	23.5	161	23.8
3-5 books	167	42.7	141	49.5	308	45.6
More than 5 books	125	32.0	74	26.0	199	29.4
Service use						
Less than 3 months	5	1.3	50	17.5	55	8.1
3-6 months	19	4.9	36	12.6	55	8.1
6-12 months	87	22.3	54	18.9	141	20.9
Over 12 months	280	71.6	145	50.9	425	62.9
Storytel use						
Less than 3 months	8	2.0	83	29.1	91	13.5
3-6 months	44	11.3	58	20.4	102	15.1
6-12 months	127	32.5	61	21.4	188	27.8
Over 12 months	212	54.2	83	29.1	295	43.6

Potential differences between the demographic and background information of the two research groups were measured with Mann-Whitney U test, a commonly used test for comparing means of two independent samples (Karjaluoto, 2007). According to the test results, there were no significant differences in gender, household size, occupation and the number of books in a month between the groups. However, the difference between the two groups was found to be significant ($p<0.001$) with age (U=43983.5, W=120619.5), service use (U=40687.0, W=81442.0) and the use of Storytel (U=32772.5, W=73527.5).

On average, the respondents in group 1 were younger than in group 2. While the mode in both groups was the option “40-49”, group 1 had more answers in options “20-29,”, “30-39” and “40-49” while group 2 had more answers in options “50-59”, “60-69” and “Over 70 years”. The comparison between the groups can be seen in Figure 5.

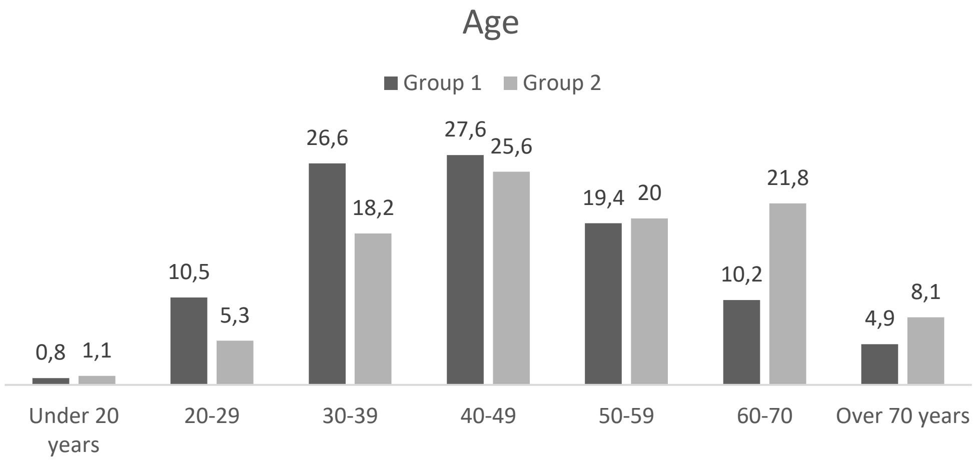

FIGURE 5 Age comparison between research groups

For questions related to service use and the use of Storytel, respondents in group 1 had more answers in the last two options "6-12 months" and "Over 12 months" compared to the other group, whereas respondents in group 2 had more answers in the first two options "Less than 3 months" and "3-6 months". The results indicate that the respondents in group 1 had more experience in using Storytel and similar services compared to group 2. The visual representation of this comparison can be seen in Figure 6.

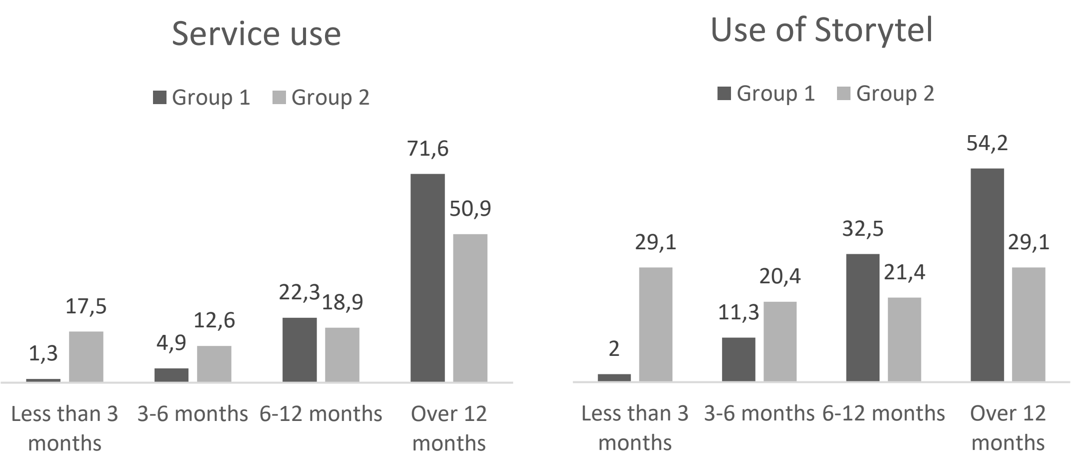

FIGURE 6 Comparison between research groups, service use and use of Storytel

The demographic information presented above need to be considered when generalizing the results of this study to a larger population. In addition, the results need to be taken into consideration when analyzing the impact of data-based value creation since they indicate that contrary to the initial assumptions, the two research groups are not identical.

For this research, data-based value creation was used as a differentiating factor between the two research groups and its impact on the research model was predicted in hypotheses H6 and H7. A dummy variable created at the beginning of the analysis was utilized for the statistical analysis to indicate the two research groups (1 = had opened the summary, 2 = hadn't opened the summary).

Before analyzing the effect of data-based value creation with a moderator effect, a T-test was conducted in SPSS to measure the potential differences of means between the two research groups. T-test is used to compare the means of two independent groups by first measuring the equality of variances and then reporting the results for both equal and unequal variances (Karjaluoto, 2007). The constructs included in the test were perceived value, payment intention and recommend intention. The equality of variances for these constructs was first measured with Levene's test. With all constructs, the null hypothesis of the variances being equal was rejected and the results of the test were read from the row "Equal variances not assumed". The results of the test can be seen in Table 4.

TABLE 4 Results of the T-test

Construct	**Group**	**N**	**Mean**	**Levene's test (Sig.)**	***P* (Equal variances not assumed)**
Perceived value	1	391	6,11	.002	.001
	2	285	5,88		
Payment intention	1	391	6,27	.000	.000
	2	285	5,83		
Recommend intention	1	391	6,29	.013	.002
	2	285	6,04		

The results state that perceived value, payment intention and recommend intention all had higher means in group 1 where the respondents were exposed to the reverse use of customer data, and that the difference between the means was significant for all three constructs.

4.2 Measurement model

Before testing the structural model for significant relationships, the measurement model needed to be verified for its internal consistency, reliability as well as convergent and discriminant validity (Fornell & Larcker, 1981; Hair et al. 2016). First, the internal consistency and reliability of the model was measured by examining the factor loadings of each construct item. All factor loadings exceeded the satisfactory level of 0.60, the lowest value being 0.784. The statistical significance of these factor loadings was measured by t-values, in which the minimum value for statistically significant results is 1.96. All of the t-values measured well above this minimum, the lowest value being 41.642. The results seen in Table 5 demonstrate good reliability for the measurement model.

TABLE 5 Factor loadings and t-values

FACTORS AND ITEMS	STANDARDIZED LOADINGS	*t*-VALUES
Perceived value		
1. Compared to the fee I need to pay, the use of Storytel offers value for my money.	0.784	46.906
2. Compared to the effort I need to put in, the use of Storytel is beneficial to me.	0.835	51.536
3. Compared to the time I need to spend, the use of Storytel is worthwhile to me.	0.856	54.548
4. Overall, the use of Storytel delivers good value to me.	0.854	59.592
Attitude		
1. I like using Storytel.	0.794	41.642
2. Using Storytel is beneficial to me.	0.862	60.356
3. Using Storytel is rewarding to me.	0.864	66.156
4. Using Storytel is sensible to me.	0.845	52.361
Payment intention		
1. I am going to continue using Storytel.	0.971	189.539
2. I predict that I could continue using Storytel in the future.	0.973	216.406
Recommend intention		
1. How likely would you recommend Storytel to a friend or a colleague? (NPS)	0.968	179.428
2. How likely would you say positive things about Storytel to a friend or a colleague? (WOM)	0.969	180.569

The internal consistency of the individual constructs was measured with composite reliability. All constructs received high values of over 0.90, which indicated good consistency inside the constructs. Average variance extracted (AVE) was used to estimate the convergent validity of the measurement model by measuring the variance captured by the construct in proportion to the variance due to measurement error (Fornell & Larcker, 1981). For the model to have good convergent validity, the AVEs should be above 0.50. Additionally, the square root of AVE should be higher than the correlation values between constructs to prove that the constructs are independent from one another (Fornell & Larcker, 1981).

In this research, all AVEs were at a satisfactory level and the square root of AVE had higher values than the correlations between other constructs, thus indicating satisfactory levels of convergent and discriminant validity. Table 6 shows the results for AVEs, construct correlations and square roots of the AVEs as well as means, standard deviations and composite reliabilities of the constructs.

TABLE 6 Average variance extracted (AVE), construct correlations, square roots of AVEs (diagonal), means, standard deviations and composite reliabilities

	AVE	1	2	3	4	5	6	7	8
PERVAL[a] (1)	0.693	**0.833**							
ATTITUDE (2)	0.708	0.729	**0.842**						
PAYINT[b] (3)	0.945	0.680	0.602	**0.972**					
RECINT[c] (4)	0.938	0.686	0.710	0.716	**0.968**				
AGE (5)	n/a	-0.015	-0.031	0.012	0.039	**n/a**			
SERVUSE[d] (6)	n/a	0.189	0.140	0.223	0.155	-0.076	**n/a**		
STORUSE[e] (7)	n/a	0.236	0.201	0.311	0.210	0.019	0.729	**n/a**	
DATA[f] (8)	n/a	-0.136	-0.143	-0.189	-0.123	0.182	-0.320	-0.411	**n/a**
Mean	-	6.022	6.174	6.089	6.186	n/a	n/a	n/a	n/a
Standard Deviation	-	0.829	0.801	1.161	0.984	n/a	n/a	n/a	n/a
CR[g]	-	0.900	0.907	0.972	0.968	n/a	n/a	n/a	n/a

Notes: [a] *PERVAL = Perceived value,* [b] *PAYINT = Payment intention,* [c] *RECINT = Recommend intention,* [d] *SERVUSE = Service use,* [e] *STORUSE = Use of Storytel,* [f] *DATA = Data-based value creation,* [g] *CR = Composite reliability, n/a = Not applicable.*

4.3 Structural model

Structural model evaluation was used to test the research hypotheses. When estimating the direct effects between variables, a path-weighting scheme was first applied. A standard bootstrapping procedure with 6800 re-samples was then used to test the significance of these paths. The graphical illustration of the empirical model path coefficients, *t*-values and R^2 values can be seen in Figure 7.

R^2 values, also known as coefficients of determination, were measured for the three dependent variables (attitude, payment intention and recommend intention) to determine the proportion of variance that is explained by the independent constructs in the model (Karjaluoto et al. 2014). According to the results, the model explains over 50% of the R^2 of all dependent variables, the highest value being for recommend intention ($R^2 = 0.569$).

According to the results, perceived value has a significant positive effect on payment intention ($\beta = 0.477$, $p < 0.01$), recommend intention ($\beta = 0.354$, $p < 0.01$) and attitude ($\beta = 0.729$, $p < 0.01$). Thus, hypotheses H1, H2 and H3 are all supported by the research data. The results also showed significant positive relationship between attitude and payment intention ($\beta = 0.216$, $p < 0.01$) as well as attitude and recommend intention ($\beta = 0.446$, $p < 0.01$), thus supporting hypotheses H4 and H5.

The effects between the two dependent variables measuring customer loyalty (payment intention and recommend intention) and the control variables (age, service use and the use of Storytel) were also tested. The results of these tests indicate that there is a significant positive relationship between age and recommend intention (β = 0.060, $p < 0.01$) as well as the use of Storytel and payment intention (β = 0.151, $p < 0.01$). The findings did not show significant results between the other four relationships that were tested. The results regarding the moderator effect of data-based value co-creation are explained in the following section.

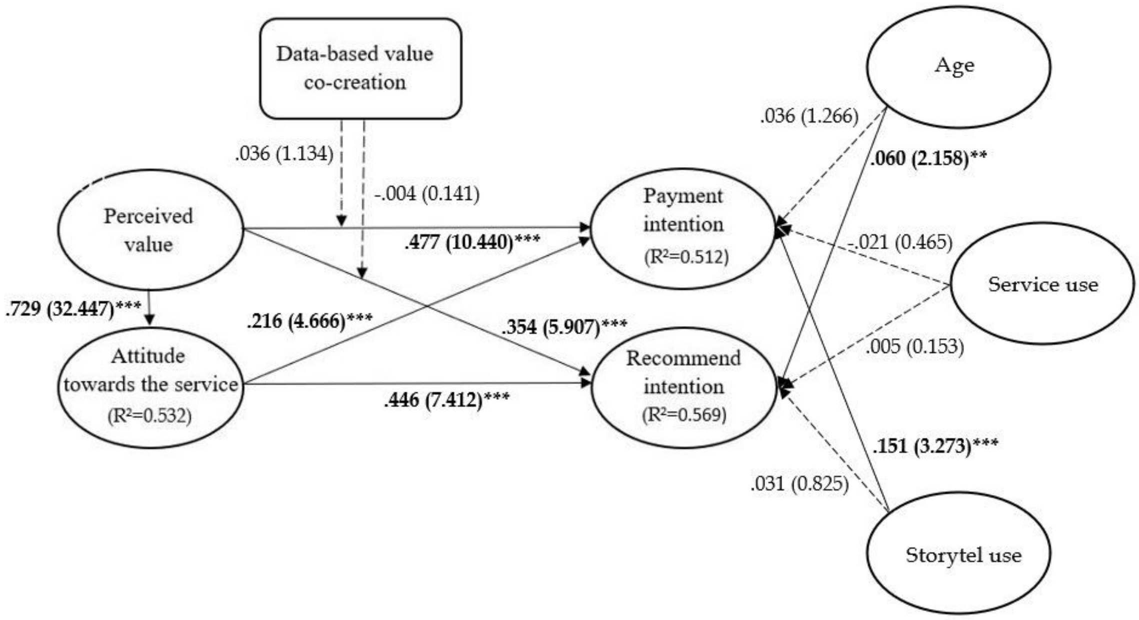

FIGURE 7 Empirical model with path coefficients and *t*-values

As mentioned in chapter 4.1, the two research groups were previously found to have significant differences between the average levels of perceived value, payment intention and recommend intention when measured with a T-test, group 1 having higher means in all three constructs. In order to test whether the reverse use of customer data could act as a strengthening factor for the positive relationship between perceived value and customer loyalty, hypotheses H6 and H7 were analyzed with Smart PLS by adding a moderator effect to the structural model.

Moderator effect can be described as a situation where an independent variable or a construct of the model has an impact on the relationship between two other constructs by changing its strength or direction (Hair et al. 2016). In this study, the dummy variable was used as a categorical moderating variable (Hair et al. 2016) when examining the impact of data-based value creation to the relationship between perceived value and payment intention (H6) and perceived value and recommend intention (H7). According to the results, data-based value creation did not have a significant moderating effect on either of the relationships mentioned earlier. Thus, hypotheses H6 and H7 are not supported. The summary of results for the structural model and hypotheses can be seen in Table 7.

TABLE 7 Results of the structural model and hypotheses

H1: Perceived value → Payment intention	**Supported**
H2: Perceived value → Recommend intention	**Supported**
H3: Perceived value → Attitude	**Supported**
H4: Attitude → Payment intention	**Supported**
H5: Attitude → Recommend intention	**Supported**
H6: Data-based value creation * Perceived value → Payment intention	**Not supported**
H7: Data-based value creation * Perceived value → Recommend intention	**Not supported**
Age → Payment intention	**Not supported**
Age → Recommend intention	**Supported**
Service use → Payment intention	**Not supported**
Service use → Recommend intention	**Not supported**
Use of Storytel → Payment intention	**Supported**
Use of Storytel → Recommend intention	**Not supported**

5 CONCLUSIONS

This chapter presents the final conclusions that can be drawn from the results introduced in the previous chapter. First, theoretical contributions are formed by answering the research questions and making other observations based on the empirical findings. Managerial implications regarding the results are then pointed out before presenting the evaluation of the research, limitations as well as suggestions for future research.

5.1 Theoretical contributions

This study investigated the relationships between perceived value, attitudes and customer loyalty measures (payment intention and recommend intention) as well as the effect of data-based value creation feature towards these relationships. The research questions for the study were the following:

How does data-based value creation affect the customer's perceived value towards the service?

How does data-based value creation affect customer loyalty in the form of payment intention and recommend intention?

To answer the research questions, a quantitative empirical study was conducted and the data for the study was collected through an online survey. The empirical part of the study was made in collaboration with the e-book and audiobook streaming service Storytel, and the context of the results are therefore most applicable to subscription services.

According to the results, perceived value was found to have a significant positive effect on payment intention, recommend intention as well as attitudes towards the service. In addition, attitude was found to have a significant positive effect on payment intention and recommend intention. It can be concluded from the results that perceived value as well as attitude towards the service are factors that both have a major impact on customer loyalty when viewed by these two metrics. Similar results can also be found in previous studies about digital products and services (Lu & Hsiao, 2010; Park & Chen, 2007; Hsiao & Chen, 2017).

The two research questions as well as hypotheses predicting the effect of data-based value creation services were assessed by comparing the two research groups to each other and by applying a moderating effect to the research model. One of the assumptions behind the research questions was that through the added value generated by the service, the customer would experience an increase in the perceived price-quality ratio of the service and would therefore be more willing both to pay for the service and to recommend it to his acquaintances. This assumption is supported by several previous research mentioned in chapter 2.3.2 (Research hypotheses), where the reverse use of customer data was said to help the company meet the customers' expectations regarding the service (Chesbrough, 2007), create value that is more diverse in nature (Saarijärvi et al. 2014) and produce both functional and economic benefits (Rintamäki et al. 2007). The social dimension of the service and the ability to pass on the information produced by the customer's own usage data were also assumed to strengthen the relationship between perceived value and loyalty.

According to the results, the average values for perceived value, payment intention and recommend intention were higher in the first research group in which the respondents had opened the summary feature containing customer data. However, the moderating effect, portraying the positive effect of data-based value creation service towards the relationship between perceived value and customer loyalty measures, did not receive significant results and was therefore not supported. These results gave an interesting contrast to the initial hypotheses and research questions, which is why further research would be beneficial to better understand the direct and indirect effects of reverse use of customer data and how these effects can change depending on the type of service and other predefining features.

One of the reasons explaining the results could be that the positive effect of the additional service on the perceived price-quality ratio was not strong enough, which is why the moderating effect of perceived value to payment intention and recommend intention did not yield significant results. The content that was produced from customer data can be assumed to be a critical tool in creating this positive effect. The information provided by the service that was the target of this research was mainly created for entertainment purposes, which made it more difficult to provide the customer with more impactful information such as tips on living a more economical lifestyle or on more environmentally friendly consumption habits. The more important the customer perceives the information to be, the more likely it is that the customer will also start to favor the service over competitors due to the additional value that they get through the information (Saarijärvi et al. 2013, 2014).

It can be concluded from the results that the reverse use of customer data can have a direct positive effect on perceived value, payment intention and recommend intention, while the use of data-based value creation service was not found to have a significant effect on the positive relationship between perceived value and loyalty metrics. With reference to the research questions, it can be said that data-based value creation can have a direct positive effect on perceived value and customer loyalty when the two are viewed as separate constructs.

Comparing the results to previous studies proved to be rather difficult due to the lack of empirical research on the effects of data-based value creation on customer value and loyalty. Most studies have examined the topic by either presenting a theoretical framework (Lim et al. 2019) or describing the phenomenon through a case company (Saarijärvi et al. 2013; Saarijärvi et al. 2014). However, the unifying factor of these previous studies is the strong assumption that reverse use of customer data can lead to higher levels of perceived value. This assumption is matched with the results of this research as the respondents who were exposed to the reverse use of customer data reported higher values of perceived value than the respondents in the control group.

Although not being part of the initial research questions, the results also gave valuable information on how different demographic qualities can affect the customer's willingness to engage in data-based value creation activities or to use such services. According to the results, age was one of these qualities since the research group that had opened the summary consisted of younger respondents than the control group. The results from this research can therefore be generalized into an assumption that older customers are less likely to use services or activities featuring reverse use of customer data. This assumption can also be explained by the fact that the younger generations of consumers are in general more comfortable with using new technology than the older generations.

The average values for customer's relationship age and experience in using similar services were also higher in the group that had opened the summary compared to the control group. This difference can be seen as an indication that the longer the customer has used the service, the more likely they are to engage in additional activities such as data-based value creation features. This seems logical as long-time customers usually experience good levels of customer satisfaction and are more committed to the company. In the context of data-based value creation, long-time customers also have created more data than newer customers and are therefore able to benefit from the service on a greater scale.

5.2 Managerial implications

The results of this research can be beneficial to service providers who are considering new ways to utilize the customer data their business processes are creating. The results are particularly applicable to subscription services that collect usage data in a continuous manner and are thus capable of creating real-time statistical information from their customers' consumption habits.

As stated in theoretical contributions, perceived value has a significant effect on attitude towards the service as well as customer loyalty measures such as payment intention and recommend intention. When comparing the two research groups, the average level of perceived value was found to be higher with respondents who had opened the summary feature. Since maximizing the company's value creating efforts is extremely important especially in more competitive markets with several providers offering similar services, these results can act as a motivational factor for businesses to start applying reverse use of customer data into their processes. Utilizing already existing resources like customer data in a new way can be a cost-effective way to help customers create more value for themselves and consequently become more loyal.

For businesses that are already utilizing reverse use of customer data in their value creation processes, the results of this research suggest that these additional efforts are likely to have an incremental positive effect on not only perceived customer value, but also on attitudes as well as loyalty measures. Although the phenomenon requires more research around what type of information results in the highest level of perceived value, following notions can already be made based on previous research: The information should be interesting, relevant and useful to the customer, preferably in a way that the information gets more accurate and high-quality the more the customer uses the service. One example of this is information related to health or economical efficiency where suggestions can be made based on purchase data or data that is generated while using the service. The more useful and accurate the information is, the stronger effect it will have on perceived value and eventually, customer loyalty.

Lastly, there are a few practical suggestions regarding the objective of this study. When it comes to the content of future Storytel2020 summary features, the academic research suggests focusing on creating information that resonates with customers' values and include metrics that they consider important and/or useful. Some examples include information related to sustainability, such as how much paper was saved due to the customer listening or reading the book in a digital form, or information about health benefits like the positive psychological effects of reading and listening to a book compared to other forms of entertainment such as watching television. The possibilities for developing more interesting information are constantly improving, and businesses collecting customer data should always look out for new ways to delight their customers with new insights of their consumption habits.

5.3 Evaluation of the research

In academic research related to business and management, reliability, replicability and validity are the most important principles when evaluating a research.

Reliability and measurement validity are especially significant in quantitative research since they act as indicators for the suitability of measures. Reliability measures the consistency of a construct and validity refers to the construct's ability to measure a certain concept (Bell et al. 2018.) The validity of the study was reinforced in the research survey by using well known metrics (NPS, WOM) as well as metrics from empirical studies in which they had been found to work well. The survey was tested with several test users, and the necessary changes were made to the survey before it was published based on user feedback.

The number of responses was adequate, which increased the generalizability of the results and made it possible to conduct several different analyses to test the hypotheses. The analysis was carried out using two software, SPSS and Smart PLS, which enabled the use of various tests for a more comprehensive set of results. SPSS was used for preliminary analysis, the analysis of descriptive qualities of demographic and background information as well as the comparison of means between the two research groups. The validity and reliability of the model was then measured, and the research hypotheses were tested with Smart PLS by using structural equation modelling (SEM).

In the confirmatory factor analysis, all factor loadings were on a satisfactory level and their significance was confirmed with high t-values, indicating good internal consistency and reliability of the measurement model. Composite reliability values measuring the consistency of individual constructs also gave good results. The convergent validity of the model was measured by AVE and the quare root of AVE was used to ensure the independence between constructs. Both measures gave satisfactory results that indicated good convergent and discriminant validity (Fornell & Larcker, 1981). Lastly, the results of this study were similar to previous studies and could further confirm their hypotheses, which can be seen as another sign of good validity.

5.4 Limitations of the research

This research has a few limitations related to the data collection method and the reliability of the results. The survey used in the empirical part of the research was targeted towards Finnish customers, so the initial measures had to be translated into Finnish and consequently some statements had to be modified to be more understandable. This could have caused differences in the respondent's interpretation since the meanings of the Finnish statements were not necessarily understood in the same way as their English counterparts.

The recipients for the research survey were selected from customers who were active users and who had access to the summary feature. Despite these criteria, the two research groups were found to be non-identical as regards to age and the previous experience in using Storytel or similar services. Although most of the respondents were active and long-time users, the respondents who had opened the summary were, on average, more experienced in using both e-book and audiobook services as well as Storytel. This can be seen as one of the reasons for the higher values of payment intention in group 1, as long-time customers usually have deemed the service to be worth their money and are thus more likely to continue paying for the subscription. In the survey, group 2 also received less responses than group 1, which can affect the reliability of comparing these two groups.

In the first research group, the survey was sent to customers who had received and opened the link for the summary feature containing customer-generated data. However, the amount of time and effort that each customer used to observe the summary feature could not be measured and therefore it is impossible to know for certain if every customer in research group 1 had read through the summary in comparison to just quickly skimming through it.

Lastly, this research focused on online subscription services, and therefore the results cannot be directly applied to other business models and industries without first considering their differences. Comparing multiple companies in different industries on their use of data-based value creation services would however be an interesting topic for future research, which is why it is also mentioned in the following chapter.

5.5 Future research suggestions

The reverse use of customer data is a relatively new research topic in marketing research. Previous research has mainly concentrated on portraying a more holistic picture of the new role of customer data within the CRM framework (Saarijärvi et al. 2013) and describing the phenomenon through investigating the underlying mechanisms of value creation and how the value is created (Lim et al. 2019; Saarijärvi et al. 2014). As the phenomenon gains more understanding and recognition, more practical research questions can be addressed in future studies.

For example, a deeper investigation on different factors that can impact the likelihood of a customer using data-based value creation services and features would be an interesting addition to the existing research framework around the topic. In addition to age and service use, these factors could include for example customer’s general interest in measuring and statistics as well as interest in technology. Information about the different motivations behind using data-based value creation services would create a wider picture of the phenomenon as a whole and help service providers detect factors that are the best fit for their customers.

Another interesting standpoint would be to investigate whether there are factors that limit customers’ willingness to participate in these services or even examine if these types of services could be harmful to customers or the company’s financial performance. The phenomenon of reverse use of customer data has largely been portrayed in a positive light by the existing literature. The negative aspects of the phenomenon should also receive attention as a notable and interesting research topic.

The empirical part of this research was conducted in the context of an online e-book and audiobook subscription service. Conducting similar research for different industries and business models would create a wider picture of how data-based value creation can be used for the customer's benefit and whether some industries have better qualifications for creating value in this way than others. The overall business environment the company operates in can be expected to have a great influence on the type of data-based information that is the most interesting to the customer. The comparison of several industries simultaneously would provide valuable insights for service providers, especially the ones that operate in more than one industry and want to provide their customers with valuable information in all these operations.

REFERENCES

Adams, J. S. (1963). Towards an understanding of inequity. *The Journal of Abnormal and Social Psychology, 67*(5), 422.

Adams, J. S. (1965). Inequity in social exchange. *Advances in experimental social psychology* (s. 267-299) Elsevier.

Aksoy, L. (2013). How do you measure what you can't define? the current state of loyalty measurement and management. *Journal of Service Management,*

Aksoy, L., Keiningham, T. L., Larivière, B., Mithas, S., Morgenson III, F. V. & Yalcin, A. (2012). The satisfaction, repurchase intention and shareholder value linkage: A longitudinal examination of fixed and firm-specific effects. Citeseer.

Almquist, E., Senior, J. & Bloch, N. (2016). The elements of value. 2016. *Harvard Business Review. September Issue.*

Alrubaiee, L., & Al-Nazer, N. (2010). Investigate the impact of relationship marketing orientation on customer loyalty: The customer's perspective. *International Journal of Marketing Studies*, *2*(1), 155.

Baker, J., Parasuraman, A., Grewal, D., & Voss, G. B. (2002). The influence of multiple store environment cues on perceived merchandise value and patronage intentions. Journal of Marketing, 66(2), 120-141.

Becker, G. S. (1965). A theory of the allocation of time. *The Economic Journal, 75*(299), 493-517.

Bell, E., Bryman, A. & Harley, B. (2018). *Business research methods* Oxford university press.

Bettencourt, L. A. & Ulwick, A. W. (2008). The customer-centered innovation map. *Harvard Business Review, 86*(5), 109.

Boulding, W., Staelin, R., Ehret, M. & Johnston, W. J. (2005). A customer relationship management roadmap: What is known, potential pitfalls, and where to go. *Journal of Marketing, 69*(4), 155-166.

Brodie, R. J., Whittome, J. R., & Brush, G. J. (2009). Investigating the service brand: A customer value perspective. Journal of business research, 62(3), 345-355.

Chesbrough, H. (2007). Business model innovation: It's not just about technology anymore. *Strategy & Leadership,* Childers, T. L., Carr, C. L., Peck, J., & Carson, S. (2001). Hedonic and utilitarian motivations for online retail shopping behavior. Journal of retailing, 77(4), 511-535.

Chu, C. & Lu, H. (2007). Factors influencing online music purchase intention in taiwan. *Internet Research,*

Davenport, T. H. & Prusak, L. (1998). *Working knowledge: How organizations manage what they know* Harvard Business Press.

De Matos, C. A., & Rossi, C. A. V. (2008). Word-of-mouth communications in marketing: a meta-analytic review of the antecedents and moderators. Journal of the Academy of marketing science, 36(4), 578-596.

Edvardsson, B., Gustafsson, A. & Roos, I. (2005). Service portraits in service research: A critical review. *International Journal of Service Industry Management,*

Fornell, C. & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research, 18*(1), 39-50.

Frow, P., Payne, A., Wilkinson, I. F. & Young, L. (2011). Customer management and CRM: Addressing the dark side. *The Journal of Services Marketing, 25*(2), 79-89.

Gebauer, H., Fleisch, E. & Friedli, T. (2005). Overcoming the service paradox in manufacturing companies. *European Management Journal, 23*(1), 14-26.

George, G., Haas, M. R. & Pentland, A. (2014). *Big Data and Management.*

Grewal, D., Monroe, K. B., & Krishnan, R. (1998). The effects of price-comparison advertising on buyers' perceptions of acquisition value, transaction value, and behavioral intentions. Journal of Marketing, 62(2), 46-59.

Grosso, M., & Castaldo, S. (2015). How store attributes impact shoppers’ loyalty: do different national cultures follow the same loyalty building process?. The International Review of Retail, Distribution and Consumer Research, 25(5), 503-515.

Gruen, T. W., Osmonbekov, T., & Czaplewski, A. J. (2006). eWOM: The impact of customer-to-customer online know-how exchange on customer value and loyalty. Journal of Business research, 59(4), 449-456.

Grönroos, C. (1978). A service-orientated approach to marketing of services. *European Journal of Marketing,*

Grönroos, C. (1982). An applied service marketing theory. *European Journal of Marketing,* Grönroos, C. (2000). Service management and marketing: A customer relationship management approach.

Grönroos, C. (2006). Adopting a service logic for marketing. *Marketing Theory, 6*(3), 317-333.

Grönroos, C. (2008). Service logic revisited: Who creates value? and who co-creates? *European Business Review, 20*(4), 298-314.

Grönroos, C. (2011). Value co-creation in service logic: A critical analysis. *Marketing Theory, 11*(3), 279-301.

Grönroos, C. & Ravald, A. (2011). Service as business logic: Implications for value creation and marketing. *Journal of Service Management,*

Gummesson, E. (1995). Relationship marketing: Its role in the service economy. *Understanding Services Management, 244*, 68.

Gummesson, E. (2011). Total relationship marketing. *Routledge*.

Gupta, S. & Lehman, D.R. (2005). Managing Customers as Investments. Wharton School Publishing, Upper Saddle River, NJ.

Hair Jr, J. F., Hult, G. T. M., Ringle, C. & Sarstedt, M. (2016). *A primer on partial least squares structural equation modeling (PLS-SEM)* Sage publications.

Hamza, V. K. (2013). A study on the mediation role of customer satisfaction on customer impulse and involvement to word of mouth and repurchase intention. *International Journal of Business Insights & Transformation, 7*(1), 62-67.

Hartline, M. D., & Jones, K. C. (1996). Employee performance cues in a hotel service environment: Influence on perceived service quality, value, and word-of-mouth intentions. Journal of business research, 35(3), 207-215.

Hoffman, D. L. & Novak, T. P. (2018). Consumer and object experience in the internet of things: An assemblage theory approach. *Journal of Consumer Research, 44*(6), 1178-1204.

Holbrook, M. B. (1994). The nature of customer value: An axiology of services in the consumption experience. *Service Quality: New Directions in Theory and Practice, 21*(1), 21-71.

Homburg, C., Steiner, V. V. & Totzek, D. (2009). Managing dynamics in a customer portfolio. *Journal of Marketing, 73*(5), 70-89.

Hsiao, K. (2011). Why internet users are willing to pay for social networking services. *Online Information Review*.

Hsiao, K. (2013). Android smartphone adoption and intention to pay for mobile internet. *Library Hi Tech, 31*(2), 216.

Hsiao, K. & Chen, C. (2017). Value-based adoption of e-book subscription services: The roles of environmental concerns and reading habits. *Telematics and Informatics, 34*(5), 434-448.

Humby, C., Hunt, T. & Phillips, T. (2004). *Scoring points: How tesco is winning customer loyalty* Kogan Page Publishers.

Jones, T. O. & Sasser, W. E. (1995). Why satisfied customers defect. *Harvard Business Review, 73*(6), 88-&.

Kaplan, D. (2008). *Structural equation modeling: Foundations and extensions* Sage Publications.

Karjaluoto, H. (2007). *SPSS opas markkinatutkijoille* Jyväskylän yliopisto.

Karjaluoto, H., Töllinen, A., Pirttiniemi, J. & Jayawardhena, C. (2014). Intention to use mobile customer relationship management systems. *Industrial Management & Data Systems,*

Karmarkar, U. S. & Apte, U. M. (2007). Operations management in the information economy: Information products, processes, and chains. *Journal of Operations Management, 25*(2), 438-453.

Keiningham, T. L., Aksoy, L., Buoye, A. & Cooil, B. (2011). Customer loyalty isn't enough. grow your share of wallet. *Harvard Business Review, 89*(10), 29-31.

Kim, J., & Forsythe, S. (2008). Adoption of virtual try-on technology for online apparel shopping. Journal of Interactive Marketing, 22(2), 45-59.

Kim, H., Chan, H. C. & Gupta, S. (2007). Value-based adoption of mobile internet: An empirical investigation. *Decision Support Systems, 43*(1), 111-126.

Kindström, D. (2010). Towards a service-based business model–Key aspects for future competitive advantage. *European Management Journal, 28*(6), 479-490.

Lehtinen, U. & Lehtinen, J. R. (1991). Two approaches to service quality dimensions. *Service Industries Journal, 11*(3), 287-303.

Leppäniemi, M., Karjaluoto, H. & Saarijärvi, H. (2017). Customer perceived value, satisfaction, and loyalty: The role of willingness to share information. *The International Review of Retail, Distribution and Consumer Research, 27*(2), 164-188.

Lim, C., Kim, K., Kim, M., Heo, J., Kim, K. & Maglio, P. P. (2018). From data to value: A nine-factor framework for data-based value creation in information-intensive services. *International Journal of Information Management, 39*, 121-135.

Lim, C. & Kim, K. (2014). Information service blueprint: A service blueprinting framework for information-intensive services. *Service Science, 6*(4), 296-312.

Lim, C., Kim, K., Hong, Y. & Park, K. (2012). PSS board: A structured tool for product–service system process visualization. *Journal of Cleaner Production, 37*, 42-53.

Lim, C., Kim, K. & Maglio, P. P. (2018). Smart cities with big data: Reference models, challenges, and considerations. *Cities, 82*, 86-99.

Lim, C., Kim, M., Heo, J. & Kim, K. (2018). Design of informatics-based services in manufacturing industries: Case studies using large vehicle-related databases. *Journal of Intelligent Manufacturing, 29*(3), 497-508.

Lim, C., Kim, M., Kim, K., Kim, K. & Maglio, P. (2019). Customer process management. *Journal of Service Management, 30*(1), 105-131.

Lin, T., Wu, S., Hsu, J. S. & Chou, Y. (2012). The integration of value-based adoption and expectation–confirmation models: An example of IPTV continuance intention. *Decision Support Systems, 54*(1), 63-75.

Lin, J. C. C. (2007). Online stickiness: its antecedents and effect on purchasing intention. *Behaviour & information technology*, *26*(6), 507-516.

Lovelock, C. H., & Wirtz, J. (2007). *Services marketing: People, technology, strategy.* Prentice Hall, Upper Saddle River, NJ.

Lu, H. & Hsiao, K. (2010). The influence of extro/introversion on the intention to pay for social networking sites. *Information & Management, 47*(3), 150-157.

Lu, H. & Lin, K. (2012). Factors influencing online auction sellers' intention to pay: An empirical study integrating network externalities with perceived value. *Journal of Electronic Commerce Research, 13*(3), 238.

Lusch, R. F. (2007). Marketing's evolving identity: Defining our future. *Journal of Public Policy & Marketing, 26*(2), 261-268.

Marketing Science Institute (2018). *Research Priorities 2018-2020.*

Mayer-Schönberger, V. & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think* Houghton Mifflin Harcourt.

McKee, D., Simmers, C. S., & Licata, J. (2006). Customer self-efficacy and response to service. Journal of service research, 8(3), 207-220.

Menon, M. (2019). GDPR and data powered marketing: The beginning of a new paradigm. *Journal of Marketing Development & Competitiveness, 13*(2)

Meyer-Waarden, L. (2007). The effects of loyalty programs on customer lifetime duration and share of wallet. *Journal of Retailing, 83*(2), 223-236.

Nardi, P. M. (2018). *Doing survey research: A guide to quantitative methods* Routledge.

Ng, I. C. & Wakenshaw, S. Y. (2017). The internet-of-things: Review and research directions. *International Journal of Research in Marketing, 34*(1), 3-21.

Ngai, E. W. (2005). Customer relationship management research (1992-2002): An academic literature review and classification. *Marketing Intelligence & Planning,*

Nguyen, B. and Mutum, D.S. (2012), "A review of customer relationship management: successes, advances, pitfalls and futures", Business Process Management Journal, Vol. 18 No. 3, pp. 400-419.

Normann, R. & Ramirez, R. (1989). A theory of the offering: Toward a neo-industrial business strategy. *Strategy, Organization Design and Human Resource Management, ,* 111-128.

Park, Y. & Chen, J. V. (2007). Acceptance and adoption of the innovative use of smartphone. *Industrial Management & Data Systems,*

Payne, A. F., Storbacka, K. & Frow, P. (2008). Managing the co-creation of value. *Journal of the Academy of Marketing Science, 36*(1), 83-96.

Payne, A. & Frow, P. (2005). A strategic framework for customer relationship management. *Journal of Marketing, 69*(4), 167-176.

Peppers, D. & Rogers, M. (1993). *The one to one future: Building relationships one customer at a time* Currency Doubleday New York.

Peppers, D. & Rogers, M. (2004). *Managing customer relationships: A strategic framework* John Wiley & Sons.

Peppers, D., Rogers, M. & Dorf, B. (1999). Is your company ready for one-to-one marketing. *Harvard Business Review, 77*(1), 151-160.

Pine, B. J. (1993). *Mass customization* Harvard business school press Boston.

Prendergast, G., Ko, D. & Siu Yin, V. Y. (2010). Online word of mouth and consumer purchase intentions. *International Journal of Advertising, 29*(5), 687-708.

Reichheld, F. F. & Sasser Jr, W. E. (1990). Zero defections: Quality comes to services. *Harvard Business Review, 68*(5), 105-111.

Reichheld, F. F. (2004). The one number you need to grow. *Harvard Business Review, 82*(6), 133.

Reinartz, W., Krafft, M. & Hoyer, W. D. (2004). The customer relationship management process: Its measurement and impact on performance. *Journal of Marketing Research, 41*(3), 293-305.

Rintamäki, T., Kuusela, H. & Mitronen, L. (2007). Identifying competitive customer value propositions in retailing. *Managing Service Quality: An International Journal,*

Saarijärvi, H., Grönroos, C. & Kuusela, H. (2014). Reverse use of customer data: Implications for service-based business models. *The Journal of Services Marketing, 28*(7), 529-537.

Saarijärvi, H., Karjaluoto, H. & Kuusela, H. (2013). Customer relationship management: The evolving role of customer data. *Marketing Intelligence & Planning, 31*(6), 584-600.

Saarijärvi, H., Kuusela, H., Kannan, P. K., Kulkarni, G. & Rintamäki, T. (2016). Unlocking the transformative potential of customer data in retailing. *The International Review of Retail, Distribution and Consumer Research, 26*(3), 225-241.

Sarstedt, M., Henseler, J. & Ringle, C. M. (2011). Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. *Measurement and research methods in international marketing* () Emerald Group Publishing Limited.

Schoenbachler, D. D., & Gordon, G. L. (2002). Trust and customer willingness to provide information in database-driven relationship marketing. Journal of interactive marketing, 16(3), 2-16.

Seiders, K., Voss, G. B., Grewal, D. & Godfrey, A. L. (2005). Do satisfied customers buy more? examining moderating influences in a retailing context. *Journal of Marketing, 69*(4), 26-43.

Shankar, V. & Winer, R. S. (2006). No title. *When Customer Relationship Management Meets Data Mining,*

Sirdeshmukh, D., Singh, J., & Sabol, B. (2002). Consumer trust, value, and loyalty in relational exchanges. Journal of marketing, 66(1), 15-37.

Thaichon, P., Lobo, A., & Quach, T. N. (2016). The moderating role of age in customer loyalty formation process. *Services Marketing Quarterly*, *37*(1), 52-70.

Thaler, R. H. (2011). Show us the data.(it's ours, after all). *The New York Times, 23,* 2011.

Thaler, R. H. & Tucker, W. (2013). Smarter information, smarter consumers. *Harvard Business Review, 91*(1), 44-54.

Uncles, M. D., Dowling, G. R. & Hammond, K. (2003). Customer loyalty and customer loyalty programs. *Journal of Consumer Marketing,* Van der Heijden, H., Verhagen, T. & Creemers, M. (2003). Understanding online purchase intentions: Contributions from technology and trust perspectives. *European Journal of Information Systems, 12*(1), 41-48.

Vargo, S. L. & Lusch, R. F. (2004). *Evolving to a new dominant logic for marketing* Routledge.

Vargo, S. L. & Lusch, R. F. (2008). Service-dominant logic: Continuing the evolution. *Journal of the Academy of Marketing Science, 36*(1), 1-10.

Vargo, S. L., Maglio, P. P. & Akaka, M. A. (2008). On value and value co-creation: A service systems and service logic perspective. *European Management Journal, 26*(3), 145-152.

Verhoef, P. C., Venkatesan, R., McAlister, L., Malthouse, E. C., Krafft, M., & Ganesan, S. (2010). CRM in data-rich multichannel retailing environments: a review and future research directions. *Journal of interactive marketing*, *24*(2), 121-137.

Vilkka, H. (2007). *Tutki ja mittaa: Määrällisen tutkimuksen perusteet*

Wang, C. Y., & Wu, L. W. (2012). Customer loyalty and the role of relationship length. *Managing Service Quality: An International Journal*.

Watson, G. F., Beck, J. T., Henderson, C. M., & Palmatier, R. W. (2015). Building, measuring, and profiting from customer loyalty. Journal of the academy of marketing science, 43(6), 790-825.

Yang, Z., & Peterson, R. T. (2004). Customer perceived value, satisfaction, and loyalty: The role of switching costs. Psychology & marketing, 21(10), 799-822.

Zablah, A. R., Bellenger, D. N. & Johnston, W. J. (2004). An evaluation of divergent perspectives on customer relationship management: Towards a common understanding of an emerging phenomenon. *Industrial Marketing Management, 33*(6), 475-489.

Zeithaml, V. A. (1988). Consumer perceptions of price, quality, and value: A means-end model and synthesis of evidence. *Journal of Marketing, 52*(3), 2-22.

Zeithaml, V. A., Berry, L. L. & Parasuraman, A. (1996). The behavioral consequences of service quality. *Journal of Marketing, 60*(2), 31-46.

APPENDIX

Appendix 1. Survey questionnaire

Books per month	
	On average, how many books do you usually read or listen to in one month? * ** Scale: 1=Less than 1 book, 2=1-2 books, 3=3-5 books, 4=More than 5 books*
Service use	
	How long have you been using online e-book and audio-book services? * ** Scale: 1=Less than 3 months, 2=3-6 months, 3=6-12 months, 4=Over 12 months*
Storytel use	
	How long have you been using Storytel? * ** Scale: 1=Less than 3 months, 2=3-6 months, 3=6-12 months, 4=Over 12 months*
Perceived value	
PERVAL1	Compared to the fee I need to pay, the use of Storytel offers value for my money. *
PERVAL2	Compared to the effort I need to put in, the use of Storytel is beneficial to me. *
PERVAL3	Compared to the time I need to spend, the use of Storytel is worthwhile to me. *
PERVAL4	Overall, the use of Storytel delivers good value to me.* ** 1 = Completely disagree, 7 = Completely agree*
Attitude	
ATTITUDE1	I like using Storytel. *
ATTITUDE2	Using Storytel is beneficial to me. *

ATTITUDE3	Using Storytel is rewarding to me. *
ATTITUDE4	Using Storytel is sensible to me. * ** 1 = Completely disagree, 7 = Completely agree*
Payment intention	
PAYINT1	I am going to continue using Storytel. *
PAYINT2	I predict that I could continue using Storytel in the future.* ** 1 = Completely disagree, 7 = Completely agree*
Recommend intention	
RECINT1 (NPS)	How likely would you recommend Storytel to a friend or a colleague? *
RECINT2 (WOM)	How likely would you say positive things about Storytel to a friend or a colleague? * ** 1 = Not at all likely, 7 = Very likely*
Gender	
	Respondent's gender * ** Scale: 1=Male, 2=Female, 3=Other, or I prefer not to say*
Age	
	Respondent's age * ** Scale: 1=Under 20 years, 2=20-29, 3=30-39, 4=40-49, 5=50-59, 6=60-70, 7=Over 70 years*
Household size	
	Respondent's household size (persons) * ** Scale: 1=1, 2=2, 3=3, 4=4, 5=5, 6=More than 5*
Occupation	
	Respondent's occupation (if you are studying and working at the same time, select the option with which you spend the most time) * ** Scale: 1=Student, 2=Employed, full time or fixed term, 3=Employed, part-time, 4=Entrepreneur, 5=Retired, 6=Unemployed*