NTNU
Norwegian University of
Science and Technology

From Blockchain Utopia to Commercial Success

A study on how blockchain-based home-sharing startups can succeed in the sharing economy

Vilde Marie Barikmo Boge
Marianne Åldstedt Nyrønning

Industrial Economics and Technology Management
Submission date: June 2018
Supervisor: Øystein Moen, IØT

Norwegian University of Science and Technology
Department of Industrial Economics and Technology Management

Problem Description

How can new blockchain-based home-sharing platforms succeed with disruptive innovation in the sharing economy?

Preface

This master's thesis is conducted as part of achieving a Master of Science in Industrial Economics and Technology Management at the Norwegian University of Science and Technology (NTNU). It was written during the spring of 2018, and contributes to fulfill the requirements for a specialization in Strategy and International Business Development. The idea of exploring blockchain technology in the sharing economy came to life in the spring and summer of 2017, due to the substantial increase in the market value of cryptocurrencies and interest in the underlying distributed ledger. Following our project thesis, which explored the impact of blockchain on the sharing economy, we identified potential benefits of using blockchain technology in sharing activities associated with high transaction costs and agency problems. Hence, as we aim to limit our scope to *one* segment within the sharing economy, home-sharing activities presented ample opportunities for exploration.

Throughout our research, we have had the pleasure of acquiring deep insight into possibly one of the most disruptive innovations of this decade. It has been truly exciting to study the blockchain technology, and in parallel experience how the technology attracts attention from the society. We believe that cryptocurrencies and blockchain technology are at the beginning of their adventure, and that we will see the technology upend how we perceive businesses and transactions. While we acknowledge that the crypto-economy is rapidly developing, we hope that our thesis is valuable for entrepreneurs with an interest in the use of blockchain technology in home-sharing, and for already established startups aiming for growth and commercial success within this sharing economy segment. Additionally, we hope to contribute with insights to managers and the general public with interest in real-life use of blockchain and cryptocurrencies outside financial markets.

This thesis was conducted under supervision of Professor Øystein Moen at the Department of Industrial Economics and Technology Management, and we would like to thank him for his excellent guidance and support. From the onset of our work, and to the final completion of our master's thesis, Øystein was always available and willing to answer our questions and contribute with prompt and constructive feedback. We truly appreciate his sharing of knowledge and the freedom he gave us in forming our own thesis. At last, we would also like thank our families for endless support, and especially give our gratitude to Jacob Aamodt for the time and effort put into assisting us throughout the work with our thesis.

Trondheim, June 11th, 2018

Marianne Å. Nyrønning Vilde Boge

Marianne Åldstedt Nyrønning Vilde Marie Barikmo Boge

Abstract

Since the commercialization of the Internet in the late 20th century, business models have been adapted and reconfigured to accommodate an era of ever-changing technological progress and shifting customer demands. One of the most successful market architectures that emerged is found in the *sharing economy*, which has materialized through our increasingly digital and connected way of living. However, customer demands are rapidly shifting, and people are sceptical towards centralized technological platforms harnessing their personal information. Moreover, the power discrepancy in the sharing economy is debated, and the safety and privacy issues associated with current sharing platforms present a significant concern. In parallel, blockchain technology is predicted to fuel the next wave of disruption in the sharing economy, by making trusted third-party intermediaries obsolete. Many entrepreneurs are realizing the potential the technology brings forth, and several blockchain-based startups are entering the home-sharing industry to challenge Airbnb.

In this exploratory and quantitative study, we investigate the potential success of blockchain-based home-sharing startups using descriptive statistics and structural equation modeling. The analysis is based on a conducted survey amongst Norwegian consumers with a total of 518 respondents, and publicly available information from Airbnb. With this, we explore the current market for home-sharing, and map the existing drivers of home-sharing usage and areas of improvements within current offerings. Thereafter, we use the framework of disruptive innovation to discuss our empirical findings. We both highlight how a potential upcoming trust shift - from trust in institutions to trust in strangers - is facilitating the adoption of blockchain-based applications, and explore the disruptive potential of blockchain technology in home-sharing.

Our results suggest that the concept of home-sharing services has reached mass-market adoption. Additionally, consumer adoption is still rising, making room for new entrants. The most important improvement areas in current platforms were identified in relation to security, safety and privacy issues. We also find that a good reputation, ID verification, safe payment systems and effortless communication is important for host attractiveness. Blockchain-based home-sharing startups should therefore emphasize on accommodating these unmet needs and demands. The optimal market entry for these startups is to deploy a low-cost strategy, and approach young men with an interest for cryptocurrencies. Our results show that blockchain-based home-sharing platforms can potentially disrupt Airbnb when technological attributes and decentralized applications become more familiar to the general consumer. However, we also find that technology complexity, regulation and legislation currently present a barrier to such mainstream adoption.

Sammendrag

Siden kommersialiseringen av Internett på slutten av 1900-tallet, har bedrifter sett seg nødt til å tilpasse forretningsmodeller i takt med stadig skiftende kundebehov og teknologiske nyvinninger. En av de mest suksessfulle forretningsmodellene som oppstod var delingsøkonomien, materialisert gjennom vårt stadig mer digitalt tilkoblede samfunn. Dagens delingsøkonomi preges av skiftende kundebehov, samt brukere som er skeptiske til å dele personlig data med tredjeparter. Samtidig har de sentraliserte aktørene i hjemdelingssektoren mottatt massiv kritikk på bakgrunn av den tilsynelatende urettferdige maktbalansen som eksisterer mellom brukere og plattform. Det finnes også usikkerhetsmomenter knyttet til brukersikkerhet og personvern. Parallelt antas den neste bølgen av disrupsjon å følge med implementeringen av blokkjedeteknologi, som muliggjør en desentralisert delingsøkonomi uten tilstedeværelsen av tredjepartsaktører. Mange gründere ser potensialet som bor i blokkjedeteknologi, og flere blokkjedebaserte oppstartsbedrifter er på vei inn i hjemdelingsindustrien med mål om å utfordre Airbnb.

I denne utforskende kvantitative studien bruker vi beskrivende statistikk og strukturell ligningsmodellering for å undersøke hvordan blokkjedebaserte oppstartsbedrifter i hjemdelingssegmentet kan oppnå suksess. Analysen er basert på en undersøkelse blant norske forbrukere med totalt 518 respondenter, samt offentlig tilgjengelig data fra Airbnb. Med utgangspunkt i dette redegjør vi for det eksisterende markedet for hjemdelingstjenester, og kartlegger drivere for bruk av hjemdelingsplattformer, samt ser på forbedringsmuligheter av dagens løsninger. Videre benytter vi rammeverket for disruptive innovasjoner til å diskutere våre empiriske funn. Vi utforsker også hvordan utviklingen fra et samfunn bygget på tillit til institusjoner, til et samfunn preget av tillit til fremmede kan åpne opp for nye og desentraliserte markedsmodeller basert på blokkjedeteknologi, samt belyser det disruptive potensialet til blokkjedeteknologi i hjemdelingssegmentet.

Våre resultater tyder på at hjemdeling som forretningskonsept har nådd massemarkedet. Det strømmer fremdeles nye brukere til tjenesten, noe som gir rom for nye aktører. De viktigste forbedringsområdene i dagens delingstjenester er knyttet til sikkerhetsspørsmål og usikkerhet med hensyn til personvern. Vi finner også at et godt rykte, ID-verifisering, sikre betalingssystemer og enkel kommunikasjon øker attraktiviteten til verter i disse hjemdelingstjenestene. I en oppstartsfase anbefaler vi at blokkjedebaserte hjemdelingsplatformer anvender en lav-kost strategi rettet mot unge menn med interesse for kryptovaluta. Våre resultater viser at blokkkjedebaserte hjemdelingsplattformer potensielt kan føre til disrupsjon av Airbnb når teknologiske aspekter og desentraliserte applikasjoner blir mer kjent for den generelle forbrukeren. Imidlertid finner vi at teknologiens kompleksitet, regulering og lovgivning fremdeles er en barriere for slik massemarkedsadopsjon.

Table of Contents

List of Figures

List of Tables

1 Introduction

The dawn of our Internet-connected world emerged with the promise of liberating information and making the economy more democratic (Ross, 2017). It also became an important driver for the emergence of the *sharing economy*, defined as the "peer-to-peer-based activity of obtaining, giving, or sharing the access to goods and services, coordinated through community-based online services (Hamari et al., 2016, p. 2047)." Amongst the biggest players in this industry is the technology giant Airbnb, which is a home-sharing platform allowing users to rent out the idle capacity of their apartments to travelers seeking short-term accommodation. However, despite several stories of success within the sharing economy, history has shown how business models in our technology-driven world are always exposed to new competitors and the threat of *disruption*. In an increasingly global and turbulent business environment, what makes firms successful today, might very well result in their downturn tomorrow.

While the Internet succeeded in liberating information, Airbnb is a clear symbol of how it failed on its promise to democratize the economy, and instead bringing us a new set of monopolistic structures (Bollier, 2015; Tomsky, 2018). Moreover, Airbnb and its competitors struggle with both security and safety issues, in addition to receiving criticism for controlling large amounts of personal data (Tapscott & Tapscott, 2016). Hence, in parallel with increased acceptance of new technologies, innovative solutions are introduced to facilitate more secure, cost-effective, rapid and decentralized online transactions. One of the most promising advancements is the *blockchain technology*. First known as the foundational core of Bitcoin, blockchain technology is poised to become the most exciting invention of this century, leading Airbnb and its equivalents on a trail of potential disruption (Tapscott & Tapscott, 2016; Makridakis, Polemitis, Giaglis & Louca, 2018).

1.1 Background

The growth of the sharing economy is powered by internet connectivity, the ubiquity of mobile devices, on-demand information and reduction of transaction costs, thus making formerly frustrating sharing activities more hassle-free (Hamari et al., 2015; Wallenstein & Shelat, 2017; Manyika et al., 2016). According to Wallenstein and Shelat (2017), more than $23 billion have been invested in the sharing economy since 2010, and Airbnb is currently valued at more than $31 billion, making it the second-most valuable startup in the United States (Thomas, 2017). Platforms in the sharing economy are situated between vast supply systems (where the costs are) and a large number of customers (where the money is) (Goodwin, 2015). This allows the platforms to generate revenues without any substantial investments. As Goodwin (2015) illustrates it "Uber, the world's largest taxi company, owns no vehicles. Facebook, the world's most popular media owner, creates no content. Alibaba, the most valuable retailer, has no inventory. And Airbnb, the world's largest accommodation provider, owns no real estate." However, without the presence of such intermediaries, sharing activities would be a far-fetched scenario, as the platform is essential to build trust between strangers and to coordinate efficient transactions (Schor & Fitzmaurice, 2015). This dependency also makes the platforms eligible to recoup a portion of the revenue that is created in the exchanges (e.g., by charging membership or transaction fees). Nevertheless, with the introduction of blockchain technology, the dynamics of the sharing economy could be drastically altered. According to Tapscott & Tapscott (2016), the very essence of blockchain disruption lies in its ability to eliminate trusted intermediaries like Airbnb.

Nine years have passed since the invention of Bitcoin, and the rapid advancement in blockchain technology arguably presents a powerful tool in disrupting business models based on providing trust between buyers and sellers (Tapscott & Tapscott, 2016; Sundararajan, 2016). Literature suggest that blockchain-based decentralized applications (DApps) have the ability to enhance personal data protection and security services (Zykind, Nathan & Pentland, 2015; Noyes, 2016), increase transparency (Pilkington, 2016), enable faster transactions (Moody's Global Credit Research, 2016), and facilitate reputation system enhancement (Dennis & Owen, 2015), thus allowing trust to be established within a system of unknown users (Piscini, Guastalla, Rozman, & Nassim, 2016). As Hal Finney, the recipient of the first ever Bitcoin, said "[With this], you can protect yourself, rather than having to trust others. This puts more power into the hands of the consumer (Greenberg, 2014)." For the sharing economy, this implies that exchanges can take place without the presence of centralized intermediaries, positioning blockchain technology as the potential solution for fulfilling the initial promise of the Internet, eliminating top-down corporations and enabling a distributed business model governed *by* and *for* the people creating value (Swan, 2015; Tapscott & Tapscott, 2016).

Technology entrepreneurship is a key driver for stimulating and sustaining economic growth, as introduction of new and complex technologies creates opportunities for startups to challenge established incumbents and rejuvenate industries (Solow, 1957; Porter, 1990). Blockchain technology is no exception, and is argued to enable disruption of any centralized system that coordinates valuable information (e.g., Wright & De Filippi, 2015; Walport, 2016). Johnston et al. (2014) even argue that "Everything that can be decentralized, will be decentralized". However, in an ever-changing technological competitive field, buzzwords like "disruption", "cryptocurrency" and "blockchains" are key ingredients to attract attention from venture capitalists (Winkler & Matthies, 2018; Alexander, 2016). This is clearly illustrated by the number of new startups and invested capital that is flowing into the market.

As of May 2018, 343 *initial coin offerings*[1] (ICOs)[2] have been launched in 2018, raising a total of $8.9 billion (CoinSchedule, n.d.a). In comparison, the total number of new ICOs in May 2017 was 59 (CoinSchedule, n.d.b), which corresponds to a growth of an astonishing 481 percent. However, the failure rate of these firms are high, and 46 percent of the startups funded through ICOs in 2017 have already failed (Sedgwick, 2018). Researchers have long noted that startups have high failure rates relative to their older counterparts (Shapero & Giglierano, 1982; Baum, Calabrese & Silverman, 2000), facing more strict resource and capacity constraints, and

---

[1] Initial coin offerings (ICO) are an alternative to the traditional fundraising-alternative (IPO), which will be presented in more depth in Section 2.1.7.

[2] A complete list of the acronyms used in this thesis is found in Appendix 1.

suffering from the liability of newness (Stinchcombe, 1965; Freeman, Carroll & Hannan, 1983). Moreover, the future success of startups depends and fluctuates with several unpredictable external factors, including economic conditions, regulations, resource constraints, changing political conditions and competition (Leidecker & Bruno, 1984).

A few decentralized home-sharing platforms already exist. However, most of the companies are still in their infancy and need to cope with traditional startup obstacles. In addition, they need to address the uncertainty regarding how consumers will react to blockchain-based trust, and how future regulations and legislations will play out. New business configurations involve considerable uncertainty, and according to Teece (2017) it takes time for business model innovation to catch up with new technological possibilities. Hence, if the predictions of the disruptive potential of blockchain shall come to life, it is essential to understand what influences the survival and growth of these new technology startups (Krabel & Mueller, 2009). Picking a fight with today's disruptors calls for careful considerations, and requires a viable business model that almost perfectly adapts to the overlooked or overserved needs in the current market (Christensen & Raynor, 2003).

1.2 Related Work and Problem Statement

Literature on blockchain technology includes a wide range of white papers and articles written by computer scientists and cryptographers, emphasizing on the current technology status and further technological advancements. However, while understanding the technical features of blockchain is crucial, these papers often lack understandable implications on how blockchain implementation could strengthen current business positions, and fails to elaborate on the disruptive potential compared to existing incumbents. The cross-industry potential of blockchain is considered huge (Moody's Global Credit Research, 2016), and some even compares it to the invention of the Internet and its comprehensive impact on almost every industry (Buehler et al., 2015; Courtneidge & Buelli, 2015; McLean, 2016). Nevertheless, in academia, the majority of scholars researching blockchain from a business perspective have emphasized on the financial industry (e.g., Fanning & Centers, 2016; MacDonald, Allen & Potts, 2016; Raskin and Yermack 2016; Peters & Panayi, 2016; Crosby, Pattanayak, Verma & Kalyanaraman, 2016; Yermack, 2017; Ito, Narula & Ali, 2017) and payment systems (e.g., Beck, Czepluch, Lollike & Malone, 2016; Rysman & Schuh, 2017). Some also exemplify how blockchain applications will move beyond financial and capital markets (e.g., Catalini, 2017a; 2017b; Swan, 2015; Wörner et al., 2016), and a few have analyzed the blockchain startup (Fiedler & Sandner, 2017) and application ecosystem (Dhillon, Metcalf & Hooper, 2017). Previous research has also focused on implications for regulations and governance (Kiviat 2015; Wright and De Filippi 2015; Walport 2016; Davidson, De Filippi, & Potts 2016) and privacy concerns (e.g., Zysking, Nathan & Pentland, 2015; Athey, Catalini, & Tucker 2017).

However, little attention has been given to how already established blockchain startups are operating across different industries (Friedlmaier, Tumasjan & Welpe, 2017). A few scholars touch upon the subject, such as Conley (2017), who makes implications for how blockchain startups most successfully can design a token and launch projects through ICOs. Allen (2017) examines how blockchain entrepreneurs are discovering the complementary institutional structures to form new decentralized frontier societies, and Chen (2017) discusses how blockchain technology and tokens have sparked a new wave of innovation, which may completely reshape entrepreneurship and innovation. In addition, Tapscott and Tapscott (2016) introduce illustrative examples of new decentralized business models, and argue that blockchain technology might drastically alter the architecture of firms. Still, seemingly none have explored how blockchain-based startups should act and position themselves in order to compete with established players.

With regards to the sharing economy, a handful of scholars present brief discussions on the possible benefits of blockchain technology, including Sundararajan (2016), Swan (2015), Puschmann and Alt (2016), Mainelli and Smith (2015), Kane (2016), De Filippi (2015), Tapscott and Tapscott (2016) and Hawlitschek, Notheisen and Teubner (2018). However, with the exception of Hawlitschek et al. (2018), who review blockchain technology with regards to trust in the sharing economy, the discussions mainly scratch the surface of blockchain utilization and adoption. Yli-Huumo et al. (2016) conducted a state of the art review on the field of Bitcoin and blockchain technology, and extracted 41 existing papers. Here, they point to a lack of research exploring the application areas of blockchain technology with regards to business opportunities, and specifically pointing to shared assets as an area in need of further exploration.

In our preceding project thesis (see Boge & Nyrønning, 2017), we contributed with in-depth insights and descriptions on how blockchain technologies could enable a true peer-to-peer sharing economy which, to the best of our knowledge, no academic literature has done comprehensively prior to our research. Moreover, we provided implications for how existing sharing economy companies should face the threat of disruptiveness from blockchain technology. Nevertheless, as the project thesis served as a general implication for the entire sharing economy, it is inconclusive in making implications for specific sectors or industries. Hence, as the financial industry has attracted most attention from researchers today, there are still many research gaps to fill outside these lenses, thus giving opportunities for more nuanced studies. As we have found no literature exploring blockchain in the peer-to-peer accommodation industry, which is currently one of the five key sharing economy sectors (PwC, 2015), this stands out as an interesting area for further exploration. Home-sharing is often associated with high risk and great chance of misconduct (e.g., asset abuse, physical violence), and trust is therefore a necessary condition for these transactions to take place (e.g., Weber, 2014; Ert, Fleischer & Magen, 2016). Thus, there should be ample opportunities to benefit from blockchain utilization, where the technology serves as the *trust machine* (The Economist, 2015) in transactions between strangers.

Blockchain technology has the potential to entice the introduction of startups that may disrupt a wide range of industries by facilitating frictionless transactions through an immutable and transparent ledger. As of today, available DApps range from applications that enables you to start a crowdfunding campaign to hauling a cab. However, as previously introduced, the failure rate of these companies is high. Consequently, with regards to home-sharing, there is a need for exploring how these startups can succeed. First and foremost; is there a market for decentralized home-sharing platforms? And if so; how should startups act in order to commercialize their ideas?

Blockchain is by many labelled a disruptive technology, which in turn indicates that there should be ample opportunities to research paths leading to success. However, to the best of our knowledge, no literature has explored this, which we consider crucial for understanding *if* and *how* blockchain-based equivalents could represent a disruptive threat against established incumbents within home-sharing. Hence, we propose the following problem statement, which we aim to answer throughout this thesis:

How can new blockchain-based home-sharing platforms succeed with disruptive innovation in the sharing economy?

As presented in Section 1.1, startups are an important source to global economic growth, through adoption of new technologies and innovations (Audretsch, 2002). However, in order to achieve commercial success and confer a reliable competitive advantage, new ideas need to be complemented with a viable business model (Teece, 2010; Amit & Zott, 2011; Lindgardt et al., 2009). Scholars have emphasized the difficulties of replacing one foundational technology with another (e.g., Leonard-Barton, 1992; Utterback, 1994), and there is a growing awareness that the most profound challenge of this process is essentially a problem of business model transition (Christensen, 2006; Markides, 2006). In line with Ovans (2015), the very essence of succeeding with disruptive innovations lies in introducing a business model that is superior to the business models used by incumbents.

1.3 Research Questions and Conceptual Model

In order to address how blockchain-based home-sharing startups can succeed with disruptive innovations, our analysis is twofold. To explore how blockchain technology could present a fruitful solution to disruption in the home-sharing sector, we assess some of the most critical aspects of business model design. Consequently, our first four research questions seek to uncover how the market for home-sharing looks like, as well as disclose its existing customer behavior, characteristics and demands (Section 1.3.1). Thereafter, we formulate two research questions with a more entrepreneurial perspective, namely emphasizing on the role of trust in home-sharing disruption, and resolving the true disruptive potential of blockchain technology within this segment (Section 1.3.2). Lastly, we introduce our conceptual model, which clearly illustrates how the different research questions relates to each other and to our problem statement (Section 1.3.3).

1.3.1 Disruptive Business Model Design Through Customer Exploration

A new business model can be crucial to commercialize and capture the value of a technological innovation (e.g., Teece, 2010; Chesbrough, 2010), and the primary challenge of technology shifts lies in the interaction between technological development and business model innovation (Markides, 2006; Chesbrough, 2010; Christensen, 2006). However, disruptive innovations entail a high degree of experimentation and risk-taking (Govindarajan and Kopalle, 2006), both in relation to how consumers will adopt the innovations and how the future market dynamics will look like (Massa & Tucci, 2013). To cope with the associated risks, Henderson (2006) claims that customer and market-related competencies have a critical role in succeeding with disruptive innovations. This is coinciding with the work of Christensen (1997), where he argues that the success of firms can be sourced back to being responsive to customers' demands, in addition to aggressively investing in technology, products, and manufacturing capabilities that satisfy the next generation of customers.

According to Teece (2010), the different elements of a business model should reflect "what customers want, how they want it, and how the enterprise can organize to best meet those needs, get paid for doing so, and make a profit (p. 172)." Business model innovation can thus be seen as an analysis where entrepreneurs evaluate both internal and external factors that enable competitive advantages (Chesbrough, 2010; Mitchell, & Coles 2003; Gambardella & McGahan, 2010). Consequently, as a step towards assessing how blockchain-based home-sharing platforms can succeed with disruptive innovations, we use elements from business model design as an instrumental tool to understand the strategic challenges and opportunities blockchain-based home-sharing startups are facing. Our approach, as displayed in Table 1, follows a customer-oriented process, in line with the initial formulation of Teece (2010). The following sections present our four first research questions in more detail.

Table 1 Elements of Business Model Design

Boge and Nyrønning (2018)	**Connected RQs**
1. Analyze the current market situation	RQ1
2. Identify customer demands and behaviour in current market	RQ2, RQ3
3. Determine benefits to the customers from using this new product or service	RQ3
4. Identify market segments to be targeted	RQ4

Step 1 - Current Market Situation

Generally, business models either seek to exploit untapped potential in new markets or explore opportunities in already existing markets (Amit & Zoot, 2012). However, with radical and emerging technologies, the commercialization process can be complex and involve a high degree of market uncertainty (Maine & Garnsey, 2006), in particular if the goal is to enter established industries with high entry barriers and market saturation (Manzini et al., 2016). Currently, blockchain-based home-sharing startups are entering a market existing of big and established players, such as Airbnb (and HomeAway), leveraging their immense networks and market dominance to obtain several advantages from consumers, suppliers and competitors (Bollier, 2015). This market dynamic may prove to be a hinder for the growth and adoption of new blockchain-based platforms, stressing the importance of analyzing the current market situation and its potential for new entrants. Using Airbnb's market as a basis, we propose our first research question:

RQ1: *What can previous developments in prices, listings and availability on Airbnb tell us about the market potential for blockchain-based home-sharing platforms?*

Step 2 and 3 - Customer Overview and Areas for Improvements

Technological innovations have historically been the driving force of increased customer benefits (Teece, 2010), and with the digital revolution in the 21st century, companies have to adapt to the needs of a more informed, connected and demanding pool of customers than ever before (Deloitte, 2014). Several scholars have looked into the underlying drivers of increased acceptance and use of sharing services. They have identified economic benefits, environmental concerns, ease of communication and growing consumer awareness as the most important aspects (Sundararajan, 2014; Botsman & Rogers, 2010; Kaplan & Haenlein, 2010; Wang & Zhang, 2012). However, little attention has been directed towards characterizing the customer-base of sharing services, and considering the immense growth and consumer adoption of disruptive platforms like Airbnb in the past decade, it is likely that the underlying drivers and characteristics of consumption gradually evolves. If Airbnb does not acknowledge or adapt to changes in consumer preferences, it could make room for new entrants to grasp for market shares.

According to Teece (2010), building a successful business model supporting such a customer-oriented approach begins with a deeper understanding of the fundamental behavior and needs of customers, how competitors are or are not satisfying those needs, and the technological possibilities and trajectories existing for improvements (Teece, 2010; 2017). As Adams (2018, p. 11) puts it: “cutting-edge technology infrastructure will not equate to market success; more important is how the technology is used.” Consequently, we present our second and third research questions:

RQ2: *What are the underlying drivers of home-sharing usage?*

RQ3: *What are the consumer demands for improvements in home-sharing platforms, and how can blockchain technology be deployed to serve these needs?*

Step 4: Market Segmentation

Falling short of understanding differences amongst potential customers, market segments and competition are common pitfalls for many businesses (Teece, 2010). In general, companies are best served with first identifying one subset or segment, instead of trying to satisfy the entire market (Ohmae, 1983), thus making market segmentation a crucial element of business model design (Teece, 2010). Additionally, new innovations can be introduced in both low-end or high-end markets, and in completely new markets consisting of customers with demands that existing offerings have been unable to fulfill (Govindarajan & Kopalle, 2006). Hence, we propose our fourth research question:

RQ4: *Which consumer segments present attractive targets for blockchain-based home-sharing platforms market entry?*

1.3.2 The Role of Trust and Blockchain Technology Disruption

The previous research questions focused on understanding customer dynamics with regards to the home-sharing market. Nevertheless, as trust lies at the heart of sharing activities (e.g., Belk, 2010; Botsman, 2017) and is the fundamental basis in online transactions (Zheng, Li & Hou, 2011; Jarvenpaa, Tractinsky & Saarinen, 1999), it is key to fully understand its impact for blockchain-based innovation. Especially as blockchain eliminates the trusted centralized intermediary, the commercialization of blockchain-based home-sharing startups could face a major barrier; the familiar notion of institutional trust needs to be replaced with a willingness to trust in the underlying cryptographic infrastructure. Botsman (2017) argues that society is in fact already entering a new era of distributed trust, which also may provide a fertile ground for blockchain-based home-sharing. However, are people really ready to trust in technology? This leads us to our fifth research question:

RQ5: *How can developments in trust impact the disruptive potential of blockchain technology in home-sharing?*

There will always exist sceptics claiming that the newly found innovation of blockchain technology is overhyped (e.g., Bloomberg, 2017; Flieswasser, 2017). This dynamic was also present when the Internet was in its infancy. For instance, in a Newsweek article from 1995, Clifford Stoll, a computer expert, even wrote: "Baloney. Do our computer pundits lack all common sense? The truth is no online database will replace your daily newspaper, no CD-ROM can take the place of a competent teacher and no computer network will change the way government works (Parr, 2015)". Still, the story that followed proved to be a tale that fundamentally altered the way businesses and governments operated across all industries, and allowed for new and disruptive business models to dramatically change the status quo.

However, the framework of disruption is initially based on ex post findings, implying that one can only assess the disruptiveness of an innovation after it has been introduced (Tellis, 2006; Govindarajan & Kopalle, 2006). Thus, while blockchain technology firmly is labelled a disruptive technology, the disruptive threat that home-sharing startups pose towards short-term rental incumbents is still uncertain. Hence, we propose our final research question:

RQ6: *What is the disruptive potential of blockchain technology in the home-sharing industry?*

1.4 Configuration of the Thesis

Based on the research questions presented in Section 1.3.1 and 1.3.2, we present our conceptual model in Figure 1, which illustrates the structure of the thesis. Chapter 2 provides a presentation of the current state of blockchain technology and existing home-sharing platform, including Airbnb and two blockchain-based startups. Thereafter, we present our literature review on disruptive innovation, the role of trust and blockchain attributes in Chapter 3. We emphasize that the theoretical foundational in this thesis is the disruptive innovation framework, which underpins the entire discussion and its implications. The first four research questions will be answered through quantitative analyses based on a conducted consumer survey, in addition to external data extracted from Airbnb. Thereafter, based on these empirical findings, and drawing from review literature in Chapter 2 and 3, the last two research questions will be addressed. The methodology behind our analyses are provided in Chapter 4, followed by a presentation of their results in Chapter 5. Together, our six research questions serve as a collective discussion of the problem statement in Chapter 6, before providing our conclusion and implications for further research in Chapter 7.

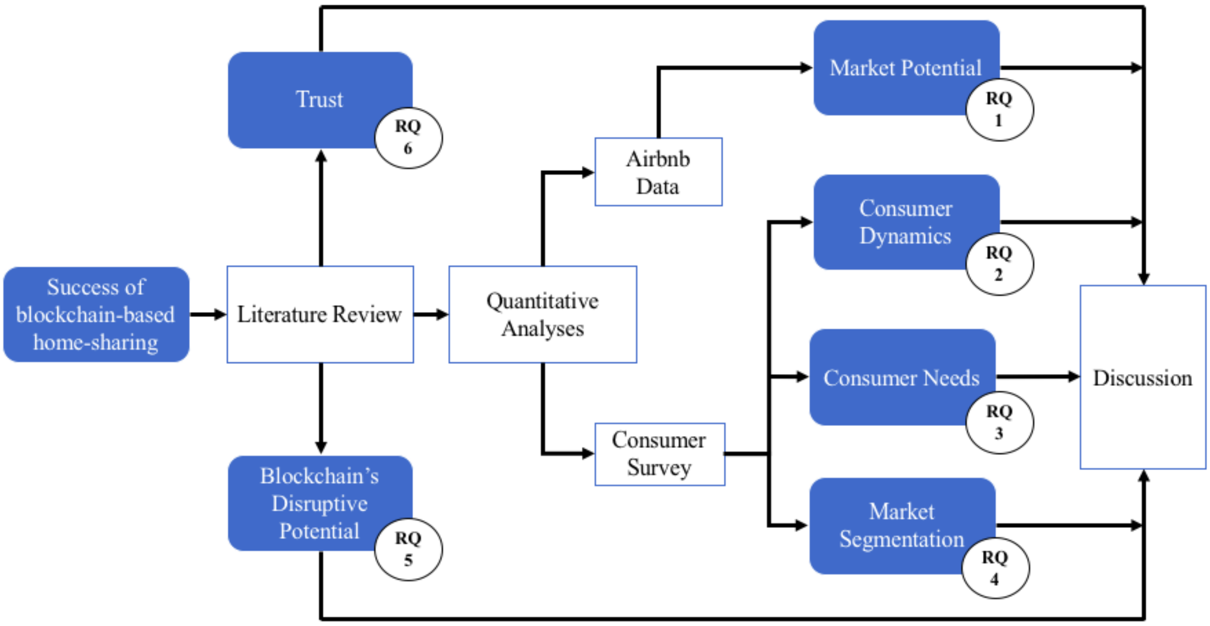

Figure 1: Conceptual model

1.5 Contributions

The contribution of our thesis is fivefold. Firstly, and most importantly, we use advanced *Statistical Equation Modeling* (SEM) to build two distinct models that respectively assess the underlying drivers of usage and need of improvements with regards to home-sharing. Thereafter, based on our empirical evidence, we discuss how blockchain attributes could be utilized in peer-to-peer accommodation, and thus also provide a solid basis for innovative business model design. By clearly relating the existing attributes of blockchain technology to real business application areas, we also contribute with an enhanced understanding of the disruptive potential of blockchain technology apart from purely conceptual considerations. Third, we shed light on the ongoing trust shift in society, and show how blockchain-based home-sharing adoption is closely linked to the new era of distributed trust. Then, we tie the preceding contributive insights together, laying the foundation for evaluating the technology and blockchain-based homesharing from the theoretical perspective of disruptive innovation. Based on this, our fifth and last contribution is our implications for blockchain-based entrepreneurs and researchers.

2 Current State - Blockchain Technology and Home-Sharing Platforms

In this chapter, we present a review of blockchain technology and home-sharing platforms. We begin the chapter by giving an introduction to blockchain technology and its technical details in Section 2.1. To give a meaningful context to blockchain technology we further present three different home-sharing platforms, starting with the industry leader Airbnb in Section 2.2, followed by two different blockchain-based startups within the home-sharing segment in Section 2.3. This chapter, in combination with the theoretical underpinnings in Chapter 3, serves as a basis for our discussion and implications regarding blockchain-based home-sharing startups in Chapter 6 and Chapter 7.

2.1 Blockchain Technology

To be innovative in an increasingly digitized business world, companies need a clear understanding of new technological concepts, and how they can alter existing business models or create new ones. Hence, in order for our readers to fully grasp the contribution of this thesis, and to be able to more precisely answer our research questions, this chapter gives an overview of the current state of blockchain technology, and the terminology underpinning cryptocurrencies and distributed ledgers.

The technical examination is based on a broad range of papers, news articles, blogs, white papers, lectures and forums, emphasizing on Bitcoin and blockchain technologies. Hence, it is challenging to reference the technical contributions properly. However, the most important literature is considered to be Nakamoto (2008), Swan (2015), Franco (2015) and Tapscott and Tapscott (2016). We accentuate that the overview of blockchain technology in this thesis is not comprehensive with regards to historical developments and technical details. For a more thorough introduction to blockchain technology, we recommend the literature listed above.

2.1.1 Introducing Blockchain Technology

In October 2008, an unknown person or group known as Satoshi Nakamoto, published a research paper on a cryptography mailing list. The paper presented the technical solution of a widely known and unsolved problem in cryptography: *the double-spending problem*. This unsolved problem had previously defeated all attempts of creating a non-centralized peer-to-peer electronic cash system (Dourado & Brito, 2014). In addition to providing code to functional digital payments, Nakamoto introduced a currency for his system, called *bitcoin*. The system allowed these bitcoins to be sent directly from one party to another, without the need of going through a trusted financial institution (Nakamoto, 2008).

To solve the problem of double-spending within a peer-to-peer electronic cash system, Nakatomo presented two radical innovations: (1) the Proof-of-work consensus mechanism[3] and (2) the distributed ledger called Blockchain (Nakamoto, 2008). While Bitcoin and other cryptocurrencies have received substantial recognition for its competitiveness relative to the traditional fiat (i.e., a currency without intrinsic value, established as money by government regulation currency), the rise of Bitcoin has also brought attention to the underlying technology empowering digital currencies. Blockchain technology, being named both an *undeniably ingenious invention*, and the *brainchild of Nakamoto*, is by many believed to be a disruptive technology (Pilkington, 2016; Wright & Filippi, 2015; Atzori, 2015).

2.1.2 Definition

Several definitions of blockchain technology exist. Wright and De Filippi (2015, p. 6) present it as "a distributed ledger or database of transactions recorded in a distributed manner, by a network of computers", whereas Tapscott and Tapscott (2016, p.435) describe it as: "an incorruptible digital ledger of economic transactions that can be programmed to record not just financial transaction but virtually everything of value". In its simplest form, a blockchain is a *decentralized* (i.e., operating without any centralized authority) database that records, updates and stores information from transactions between participating peers, and broadcasts it to the network (Nakamoto, 2008; Franco, 2015). Hence, it differentiates from a centralized ledger, where all transactions between peers are mediated through a third party. This is illustrated in Figure 2.

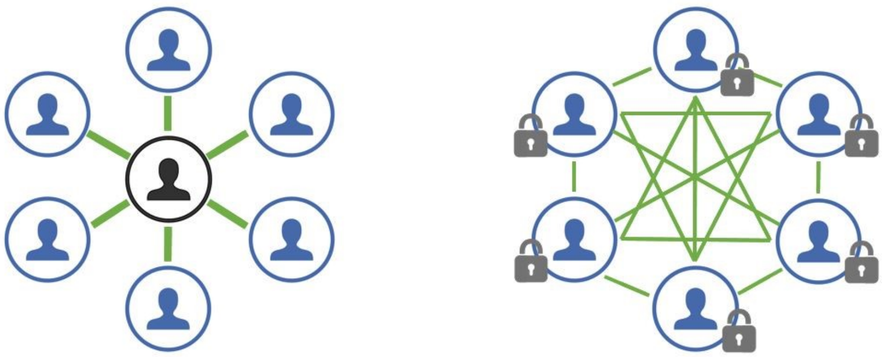

Figure 2: Centralized versus decentralized ledger

In order for blockchain to implement the flow of information to the system, it is dependent on a network of participants (called nodes) to update the system. These nodes collect unverified

[3] The Proof-of-Work mechanism works as a complement to the blockchain by requiring network nodes to solve computationally-intensive mathematical problems before they can validate a particular block of transactions, which improves the system's security (see Davidson et al., 2016; Johnston et al., 2014).

transactions and group them together in blocks through a process called mining[4]. These blocks (i.e., small encrypted data sets of transactions) are then recorded and timestamped one after another, creating a chain of blocks; the blockchain. To be able to achieve independent verification of the information existing on the blockchain, each network node stores its own copy of the ledger. The copy is automatically downloaded when users join the blockchain network, and all new transactions are updated through the participation of nodes in the network.

2.1.3 The Cryptocurrency Technology Stack

It is important to be aware of the different layers of the cryptocurrency network, also known as the cryptocurrency stack (see Figure 3), representing the general structure of cryptocurrencies (Swan, 2015). This terminology can be confusing, mostly because the blockchain industry is using several terms interchangeably, as they are still trying to establish what the different layers eventually will consist of (Swan, 2015). By using Bitcoin as an illustrative example, the blockchain is the underlying technology (i.e., a decentralized transparent database of transaction records, shared by all network nodes, updated by miners, monitored by everyone, and owned and controlled by no one), whereas Bitcoin is the protocol that runs over the blockchain, representing the software that transfers the money over the ledger. The protocol also defines the rules of cryptocurrency generation and distribution. On top of the protocol we find the bitcoin currency (BTC), which is traded in exchanges from different cryptocurrency wallets[5] or on cryptocurrency exchanges.

In order to transfer bitcoins over the network, the concept of *private-public key cryptography* is used (Tapscott & Tapscott, 2016), which means that every bitcoin holder has both a private and a public key connected to their cryptocurrency wallet. In a similar analogy to how anyone can know your email address, everyone can also see your public key, and send you cryptocurrencies. However, to collect these funds, you need to unlock them with your private key (just like the password to your email) (Khatwani, 2018).

Blockchains can be implemented both as public, permissioned and private, depending on the particular use case (Seth, 2018). The most ambitious kind of blockchain is a public blockchain, such as Bitcoin. In these, anyone can get access to the network, use its cryptographic keys, and become a node or a miner. Therefore, everyone can essentially read the information on the ledger, and make legitimate changes or add information to the chain (considering they follow the rules of the network). Hence, Bitcoin and other public blockchains are characterized as fully decentralized. However, blockchains can also be built as permissioned, meaning that you need

[4] Mining is a three stage process of verifying transactions. First, computers collect a few hundred pending transactions and turn them into a mathematical puzzle. Secondly, miners (e.g. computers) try to solve the puzzle, and the first miner to solve the puzzle broadcasts this to the network. Lastly, the other miners have to verify that the puzzle has been solved correctly through consensus, and the block is then added to the ledger (S., L, 2015).

[5] A cryptocurrency wallet is a piece of software that allows the owners to manage and spend funds from their digital funds of cryptocurrencies (e.g., bitcoins). These wallets are also incorporated onto a blockchain infrastructure, and holds the amount of funds available for each cryptographic address (Franco, 2015).

permission to read the information and serve as a validator (node or miner). One could also limit the parties able to transact via the network. Developers and entrepreneurs building permissioned blockchains essentially have a lot of freedom to experiment with the technology (e.g., who should have access, who should be able to serve the network's security, transaction verification or mining), making the solution partly decentralized. Nevertheless, in order to ensure that the validation of the transactions are governed by someone other than the initial founder(s), it is considered essential that permissioned blockchains incorporates a consensus mechanism (e.g., Proof-of-work or similar). Ledgers operating without consensus of the participants are characterized as private or shared ledgers (i.e., not decentralized).

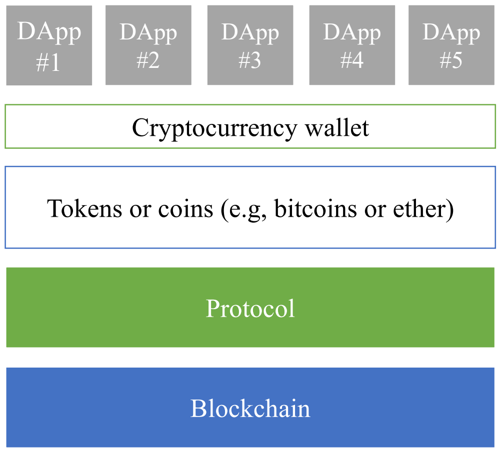

Figure 3: The cryptocurrency stack

2.1.4 Cryptocurrencies

As Bitcoin is an open source software, the programming code is available to everyone. As a result, several cryptographers and computer scientists have founded their own cryptocurrencies. Even though Bitcoin became the first cryptocurrency, hundreds of other currencies, such as *Ethereum, Ripple* and *Litecoin*, have later been developed (Wilmoth, n.d.). As of June 1st 2018, 1640 different cryptocurrencies are available for trade, with a total market capitalization of approximately $336 billion (Coinmarketcap, 2018).

A cryptocurrency is a digital representation of value functioning as a means of exchange between two or more parties, secured through advanced cryptographic algorithms. These currencies have no manifestation in the real world, and is not necessarily attached to a fiat currency. In the context of cryptocurrencies, the term *currency* is used to denote "a unit of value that can be earned and used in a certain economic system," which is then likely to be fungibly tradable into other economic systems (Swan, 2015).

While the taxonomies are often used interchangeably, cryptocurrencies are classified as either *coins* or *tokens*. The prior is simply explained as a digital asset functioning as a currency (e.g., bitcoin or litecoin), whereas tokens are an abstraction that represents ownership of an underlying tradable asset. The difference can be explained by drawing an analogy to the physical world; you pay $10 at an arcade center, effectively exchanging your currency for five "arcade coins" (representing tokens) to a specific amusement (representing a DApp). Hence, you are allowed to play this amusement five times, or maybe you can exchange your five coins for three coins giving you access to what you perceive to be a better activity. If you believe the game you have access to will become more popular in the future, you might save your coins and try to sell them with a profit later.

2.1.5 Smart Contracts

Nakamoto's original cryptocurrency structure involved three steps. Only two of them were included in the Bitcoin network; the blockchain and the Bitcoin protocol, thus missing the third part known as Turing-completeness. A Turing machine[6] is the mathematical concept of a machine that could calculate anything, given that it has access to unlimited memory (Díaz & Torras, 2012). Turing-completeness is thus the ability of a system to simulate a Turing machine (i.e., the ability to calculate everything), and a programming language is Turing-complete if it is theoretically capable of expressing all tasks accomplishable by computers. Nevertheless, while Bitcoin does not hold this feature, the Ethereum network, launched by Vitalik Buterin in 2014, has succeeded in delivering the last step of the cryptocurrency structure. In effect, the Ethereum network is the first fundamental underlying infrastructure platform that is able to run all blockchains and protocols, presenting a unified universal development platform (Swan, 2015). In practise, this means that anyone who wishes to build DApps (see Section 2.1.6) can do so on top of the Ethereum through a mechanism called *smart contracts*.

A smart contract is a self-executing contract that is designed to enforce the terms of an agreement created between two parties. Essentially, the contracts are pieces of programmable code (forming a contract written on "digital paper") that are executed by nodes on the Ethereum blockchain every time the terms of the agreement are fulfilled. The concept was first introduced by Nick Szabo in his 1997 paper entitled "The Idea of Smart Contracts", were he drew an analogy to a vending machine, which, unlike a person, behaves according to a pre-coded algorithm. When the machine verifies your deposit, your item is immediately released, without the possibility of the machine not complying with your order (except when it is broken). Furthermore, Szabo (1997) argued that smart contracting goes far beyond the vending machine, and proposed that contracts can be embedded in all sorts of property that is valuable and digitally controlled. In addition, he stated that smart contracts could provide much better observation and verification where proactive measures fall short. However, what Szabo lacked in 1997 was the technology required for this concept to manifest itself in practice.

With a Turing-complete Ethereum network, Szabo's idea could finally be put into practice. According to Buterin (2014), smart contracts represent "the simplest form of decentralized automation, and is most easily and accurately defined as (...) a mechanism involving digital assets and two or more parties, where some or all of the parties put assets in, and assets are automatically redistributed among those parties according to a formula based on certain data that is not known at the time the contract is initiated." However, smart contracts are not radical in a way that enables what previously has been impossible. Instead, it diminishes the need of

[6] The name is derived from Alan Turing, the inventor of what is considered to be the first computer.

trust in contractual issues, and thus, minimizes the impact of human judgement and biased or untrustworthy behaviour. The smart contract is both defined and executed by the code (see Figure 4). Hence, the main differentiator is the removal of risk related to each party not trusting that the other party will fulfil its side of the obligation. In effect, the smart contracts concept is applicable for a wide variety of business models involving contractual agreements.

Two parties make an option contract, e.g., a rental agreement, written in programmable code and placed on the blockchain.

A triggering event hits, e.g., an expiration date, a strike price, access to external information, and the contract executes itself according to the coded terms

As the blockchain is publically available (while the parties transacting are anonymous), exploration of activities on the blockchain is possible while maintaining the privacy of individual actors'

Figure 4: Smart contracting using blockchain technology (adapted from Rosic, 2016)

2.1.6 Decentralized Applications

The blockchain and its functionality through decentralized payments and smart contracts serves as a solid basis for the emergence of new distributed business models, with decentralized governance and trust infrastructure. In addition, blockchain technology gives innovators the capability of creating digital tokens to represent scarce assets, and democratize entrepreneurship by giving entrepreneurs a new way to raise funds and engage stakeholders. These capabilities consequently expand the disruptive potential of blockchain technology (Tapscott & Tapscott, 2016). In such, blockchain technology could represent a paradigm shift in the very idea of our business environment, potentially reshaping the landscape of entrepreneurship and democratizing innovations. Blockchain technology is giving startups new ways to develop, deploy, and diffuse decentralized applications, offering enhanced transparency, security and distribution of economic power (Swan, 2015; Chen, 2017).

As the rules of the game are changing, DApps stand out as one of the solutions to how blockchain technology could be explored and utilized in order to bring its predicted benefits to life. DApps are applications that are running on top of either established or customized Turing-complete blockchains, where pre-programmed smart contracts behave as self-enforcing operations linked to the distributed ledger. Simply put, a DApp is smart contracts with additional user interface (Swan, 2015).

According to Johnston et al. (2014), a DApp needs to have three features. First, it must be open source, operate autonomously with no entity controlling the majority of its tokens, and all data and records associated with its operation must be cryptographically stored in a public, decentralized blockchain. Secondly, the applications must generate some or all of its coins (ether or other tokens) according to a standard cryptographic algorithm at the beginning of its operations, which will function as a "money" in exchanges on the application. The creation of coins can be done through mining (like in Bitcoin), or through ICOs (see Section 2.1.7). The nodes that validate the transactions performed through the network, are reimbursed in tokens. Third, changes or improvements in the application must be implemented after consensus is established between its users (through procedures such as proof-of-work or proof-of-stake, see Johnston et al., 2015 for details).

Swan (2015) argues that a DApp in many ways can be compared to our existing traditional web applications, since both make use of programming languages such as (or similar to) HTML, CSS and Javascript in the front-end web development. When a traditional app (i.e., Facebook) needs to access its database (the back-end), it goes through an *application programming interface* (API), which is a set of instructions, protocols and tools that enable communication between various software components. A DApp has a similar structure, but with different components. It is not the API that is the interface between the front-end (the app) and the backend (the database), it is a smart contract, being the link between the DApp and the Blockchain ledger that the DApp is built upon (and where data is kept and eventual transactions are submitted). In addition, a DApp has its backend running on a decentralized peer-to-peer network, while the backend of a traditional is running on centralized servers.

Bitcoin represent the first ever made DApp for payments, with bitcoin as its token. Ethereum is on the other hand a DApp for developing and executing smart contracts, with *ether* as its token. However, the tokens distributed and used in a DApp (often called App Coins) only have fundamental value if the DApp has practical value to humans. In business literature, it is known that the higher the *perceived value*, the more competitive the product (Hollensen, 2008). However, since a cryptocurrency has no intrinsic value, the value any user pays for the currency is only the perceived value of its current worth and growth potential (i.e., bitcoins have only gained their value because society is willing to give it to them).

2.1.7 Initial Coin Offerings

Throughout 2017, and in the beginning of 2018, we have witnessed a substantial increase in startups built on blockchain technology, and like any other entrepreneur seeking investors, the crypto-projects also need funding to execute their business objectives. Hence, ICOs emerged as an alternative to traditional fundraising-alternatives. This activity is also referred to as token or crowd sale. As introduced in Chapter 1, the number of ICOs are growing rapidly. Hence, understanding the dynamics of ICOs are crucial to comprehend how cryptocurrency and blockchain-based projects obtain funding, as well as to understand why many of the ideas never achieve operational status.

The main premise of an ICO is that the blockchain-based company creates a coin or a token which is subsequently offered for sale to the public. However, acquiring coins or tokens through an ICO does not necessarily grant ownership in the project (as with the more traditional initial public offerings, IPO). Instead, the utility of holding the tokens can result in future benefits if the value of the token increase due to an increase in its perceived market value.

Initially, anyone can participate in an ICO, which inevitably will allow or a great deal of unprofessional investors to get involved in risky investments. In comparison, when a traditional company wants to be listed for public trading on the stock exchange (i.e., an IPO), there are many mandatory requirements, such as registration with the regulatory authority, legal documents and being able to show to a solid track record. In contrast, most ICOs are neither bounded by any legal requirements, nor needing to show to a solid track record. The most common procedure for companies issuing an ICO is to provide a *whitepaper* outlining the purpose and mechanism of their project or idea, often conceived by the developers.

2.2 The Traditional Home-Sharing Platform

In order to see the emerging blockchain-based home-sharing platforms in the light of a more meaningful context, we present a review of the current home-sharing market industry leader, Airbnb. An overview of two new decentralized home-sharing startups follows in Section 2.3.

2.2.1 Introducing Airbnb

Airbnb is an online marketplace through which individuals become *hosts* by renting out their private residences to travelers (i.e., guests) (Zervas et al. 2015). This idea of monetizing the idle capacity of your apartment came to life in late 2007, when Brian Chesky and Joe Gebbia (two of the founders) moved from New York to San Francisco, unemployed and eager to make a living. During a local design conference, where incoming participants were struggling to find accommodation, the duo saw an opportunity to make some money. With the spirit of pioneers, they launched AirBedAndBreakfast.com, where they offered accommodation on air mattresses in their own loft apartment for $80 a night. Fitting the air mattresses into their loft apartment, the roommates shortly after welcomed the world's first Airbnb guests. After their first successful lodging, Brian and Joe realized they could be on to something big. Hence, they continued to focus their efforts around big events, conferences and festivals. And their big breakthrough came when they targeted the Democratic National Convention in Denver in 2008. To attract attention to their website, they made Obama O's and Cap'n McCains cereal boxes, and sold them on the street and on convention parties for $40 a box. As each box had information about AirBedAndBreakfast printed on the cover, 600 people ended up staying at Airbeds during the convention, resulting in a $30,000 profit for the Airbnb founders (Schafer, 2017).

Airbnb's mission is to facilitate unique travel experiences, where travelers are allowed to connect to local cultures, people and facilities. With a valuation of $31 billion, it surpasses the valuation of renowned global hotel chains such as Hilton and Hyatt, leading airlines like United Airlines and American Airlines, and online travel companies as Expedia and Ctrip (Ting, 2016). With more than 4 million listings in over 191 countries worldwide (Airbnb Newsroom, n.d), Airbnb is the second most valuable startup in the US, only surpassed by Uber (Thomas, 2017). Lately, Airbnb have also expanded their offering to include luxury vacation rentals (Shallcross, 2018), superhosts status (Airbnb, n.d.b) and is entering the market for local experiences.

By providing a platform for peers seeking or providing private accommodation, Airbnb greatly reduces the searching, information and decision costs of these exchanges (Fradkin, 2017). Consequently, they also recoup some of the value creation in the network to finance their operations. Hosts are usually charged a 3 percent fee to cover the cost of processing payments, while the guests are charged a 5-15 percent fee, depending on price, length and characteristics of the stay (Airbnb, n.d.a).

Online exchanges are dependent on trust as an enabler to evade consumer uncertainty and transaction complexity (Friedman et al., 2000; Jarvenpaa, Tractinsky & Saarinen, 1999; Botsman & Rogers, 2010). In order to facilitate trust between strangers engaging in online transactions, Airbnb has implemented several trust enhancing mechanisms, including profile pictures and personal descriptions of users, user verification and centralized online payment systems. The platform also provides a $1 million guarantee for its hosts and guests (Airbnb, n.d.g). Still, it is the reputation system on Airbnb's platform that is considered its most valuable trust asset (Newman & Antin, 2016), where hosts and guests are encouraged to leave a review of each other upon completion of the stay. This review system includes ratings of several distinct parameters, such as the ease of communication, the punctuality of the host, cleanliness and location of the listing, the overall value, and a personal note for a more nuanced feedback. Up until July 2014, Airbnb collected and published reviews upon submission, meaning that the last reviewer could take the other party's submitted review into consideration. However, to limit strategic ratings (i.e., biased ratings affected by insights to the other party's review), Airbnb changed their reputation system, so that both parties' reviews reveal simultaneously, or 14 days after the check-out date, when no further reviewing is allowed (Airbnb, n.d.c). An interesting side note on the reputation system is that it does not really benefit the people who leave the reviews; instead it validates the members of the community and benefits future hosts and guests (Newman & Antin, 2016)

2.3 Blockchain-Based Home-Sharing Platforms

Blockchain's potential to eliminate intermediaries can affect some of the largest technology companies (Lundy, 2016). To illustrate this potential, Tapscott and Tapscott (2016, p. 137) introduce a fictional company called *bAirbnb,* which is a blockchain based DApp built on smart contracts. bAirbnb provides a user experience almost identical to Airbnb, but arguably outperforms its traditional equivalent in seven key areas: (1) reputation, (2) identity verification, (3) privacy protection, (4) risk reduction, (5) insurance, (6) payment settlement, and (7) property access using smart locks. As the following review of two blockchain-based startups shows, several entrepreneurs have realized bAirbnb's beneficial value proposition. CryptoCribs and Beenest are both home-sharing platforms utilizing blockchain technology to bring the promises of bAirbnb into life. These platforms are currently in a early operational or pre-launch phase, and the reviewed material mainly consist of information from the firms whitepapers or websites, which consequently results in a overview that is influenced by their own opinions.

2.3.1 Beenest

Beenest is a blockchain-based, commission-free and community-driven version of Airbnb, which has raised $15 million through a three-staged ICO in 2018 (Beenest, 2018a). The decentralized platform is currently aiming to solve problems related to security, reputation management and high fee-structures that exist in centralized home-sharing platforms (Beenest, 2018b). In order to achieve this, they have created their own *Bee Token*, offered to the public through the mentioned ICO. 15 percent of the total token supply is still locked up for the advisors and the team that created the platform. Consequently, as the token gains traction, its perceived value will increase (see Section 2.1.6), which will benefit the token holders.

The Bee Token will function as a value of exchange on top of three protocols built on top of the Ethereum blockchain: Payment, Arbitration and Reputation (PAR protocol). The Payment protocol allows users to pay hosts for the bookings on the platform. In order to initiate a booking, both guests and hosts transfer an agreed upon number of Bee Tokens to a smart contract. If the stay is completed without any disputes, the tokens are allocated to the correct wallet address. However, if a conflict occurs, the tokens are not allocated before the parties reach an agreement. If they fail to solve the conflict, they can allocate a flat number of Bee Tokens to the Arbitration Protocol, which initiate a conflict-solving process in the network. Once this is done, a pool of five independent Beenest users are chosen as judges based on a preset algorithm. They will have to cast a vote from 1-5, which states how much of the initial amount that should be allocated to the different parties (the judges will be rewarded with tokens for their contribution). A score of 1 indicates that 0 percent is refunded to the guest, and 100 percent to the host, whereas 2 returns 25 percent to the host and 75 percent to the guest, and so on. The median of this score will decide the final allocation of the disputed amount.

The third pillar, the Reputation Protocol, is implemented in order to ensure increased security and trust on the platform. This system provides individual reputation scores to users on a scale from 0 to 100. The lowest score (0) means that a user has completed the initial sign up process (e.g., provided their name, email, home address and birth date), but failed to provide a wallet address. When the user provides a wallet address and completes the authentication process of his or her identity, the users reaches the second level reputation score (1-5). However, it is not until the user reaches the third level (6-10) that they are allowed to complete a booking. This level requires a valid proof of identification, such as a driver's license or passport. Whenever a user has completed a booking as a host or guest, they reach the fourth reputation level (11-20). The highest reputation level (21-100) is reached the first time they submit a review to the platform. As users move up the reputation ladder, they will see positive effects in relation to lower security deposit and cancellation fees (Beenest, 2018a).

The review and feedback systems of Beenest looks a lot like the Airbnb system, with one exception. All reviews submitted after checkout are stored on the blockchain through the Beenest Reputation Protocol. In order to ensure immutability and prevent modification of these reviews, they are stored off-chain (e.g., a sidechain) with only a “link” (essentially called a hash-function) to the review being published on the blockchain. Prior to publishing the reviews to the network, they will undergo a pattern detection process that flags any racist or inappropriate reviews. If such a review is detected, it will not be posted to the network and decrease the reputation score of the user that wrote it. In extreme cases, such events can result in exclusion from the network (Beenest, 2018a).

Beenest is committed to charge a zero percent commission fees to all hosts and guests using Bee Tokens. However, if users want to pay with Bitcoins/Ether or fiat currencies (e.g., USD or Euros) they will be charged 1 percent or 3.99 percent in transaction fees, respectively. A small part of every transaction (a few cents per transaction) is extracted to complete the transfers. In order to cover the cost of host liabilities (e.g., an insurance scheme), Beenest will also charge a nominal fee, which is currently an unspecified value (Beenest, 2018a).

Beenest aims to reach the cryptocurrency community by targeting events and conferences, and engage in post-conference networking. Additionally, they are going to engage ambassadors that are rewarded tokens for their contributions to the platform. The tasks of these ambassadors will range from planning events, developing marketing programs and collect feedback and ideas from the community. The feedback will be used to develop new use-case applications. The last piece of their user acquisition strategy is to develop a referral program, which rewards users with Bee Tokens whenever they convince a new host to list their property on the site and complete a booking. Additionally, they are contacting Airbnb Superhosts in the San Francisco area, asking them to switch to their platform. Within the launch date of their platform in 2019, they aim to attract at least 50 of these hosts (Schiller, 2018).

2.3.2 CryptoCribs

CryptoCribs is a blockchain-based startup aiming to improve the modern travel experience by liberating rental markets, empowering individuals and building a strong community (CryptoCribs, 2017). They launched their platform in September 2017 after marketing themselves on the internet forum Reddit, and without the need of an ICO (Delahunty, 2018). The platform is currently listing over 1500 different properties throughout the U.S., Europe, Australia and Asia (Redman, 2018). Cryptocribs initially function as partly centralized, but aims to liberate the rental market by disintermediating themselves through a three stage network evolution process. Initially, they will function as Craigslist (e.g., the American equivalent to Finn.no), where no previous transactions or reviews are stored. Consequently, every user that transacts on the platform is treated as a new node. As bookings are completed, the reviews and transactions are recorded on the blockchain ledger, and CryptoCribs will transition to the well-known "Airbnb state". In order for CryptoCribs to enter a fully decentralized state, the transactions that flows through the centralized hub need to be replaced by peer-to-peer exchanges. However, prior to connecting the peers in the network, CryptoCribs will ensure the trustworthiness of the users by forcing them to perform ten transactions through the centralized state. As they exceed 10 transactions, the users will be characterized as trusted nodes, which enables them to engage in a direct relationship with its connecting peer through a smart contract. In this final decentralized state, users can choose to book accommodation through the platform (i.e., through the centralized "trusted" hub), but they are also free to book directly from a host through the blockchain. This is in contrast to Airbnb, where e-mail addresses and phone numbers are anonymized (Airbnb, n.d.d), which makes transacting outside the platform difficult.

In the early phases of their operations, CryptoCribs started off with a 10 percent service fee that was split equally between the host and the guest (CryptoCribs, 2017). However, every time a host or guest in the network completed a booking, and got a five-star review, the service fee dropped. These fee reductions follow a pre-set schedule, where the first 10.000 transactions in the network will decrease the service fee by 0.2 percent. When the threshold of 10.000 transactions is reached, the fee reduction will drop to 0.1 percent. By implementing this scheme, the early adopters of the platforms will be rewarded for their commitment. Additionally, these fees generate revenues to the platform creators.

CrypopCribs has no own cryptocurrency token, and has limited their payment systems to Ether and Bitcoin, wishing to build a worldwide community of cryptocurrency enthusiasts. By connecting individuals with an interest for cryptocurrencies, Cryptocribs hope their users will exchange ideas, code and discuss new projects, fueling a further development of the crypto-community. In an interview from 2018, the CEO of the company said that their "target audience is pretty much the very first community of Airbnb, a small segment of sophisticated people, who just want to host people they identify with (Whitby, 2018)". As of today, approximately 90 percent of the hosts enrolled on the platform are male Airbnb hosts in the age range from 25-35 years. In order to reach a wider audience, CryptoCribs has been integrated into the Toshi Mobile App (Whitby, 2018). Toshi is an app for digital payments in the Ethereum network, built to facilitate universal access to financial services (Toshi, 2017). The app essentially functions as a web browser that allows people to access Ethereum-based DApps.

3 Theoretical Framework and Technological Perspectives

The upcoming sections present the theoretical and empirical basis needed to discuss our research questions in Chapter 6. The chapter consists of three parts. First, in Section 3.1, we review literature on disruptive innovations, which serves as the main theoretical framework of this thesis. Thereafter, considering the role of trust in sharing activities, Section 3.2 presents the historical developments of trust, and describes how a new era of distributed trust could be paving the way for blockchain adoption. Lastly, to facilitate a discussion on how blockchain technology can be utilized to enhance different aspects of home-sharing services, we describe some of the key attributes of blockchain technology in Section 3.3.

3.1 Disruptive Innovation Theory

In an article from 1995, Bower and Christensen introduced the concept of *disruptive innovations* in an attempt to more accurately describe the phenomena where leading incumbents failed to stay on top their industry whenever certain new technologies were introduced. Since then, the concept of disruptive innovations has impacted management practises and evoked a rich debate within academia. This has resulted in a deeper understanding on what causes disruptive innovations, and how entrants and existing players should adapt to it. As of today, the theory on disruptive innovations is a guiding star for both entrepreneurial visionaries and well-established incumbents, providing them with a powerful framework for innovation-driven success (Christensen, Raynor & McDonald, 2015). The upcoming sections will provide an overview of what disruptive innovations are, how the theory has been developed as new insights have gained acceptance, and what characterizes entrant’s way of disruption.

3.1.1 Disruptive versus Sustaining Innovations

Today, businesses need to search for different kinds of improvements to maximize profits and improve their service offerings. Scholars argue that such improvements can be classified as either *sustaining* or *disruptive* (Christensen, Raynor & McDonald, 2015). While sustaining innovations points to small *incremental* changes in existing products or design, the concept of disruptive innovations has historically been the popular notion on radical innovations promoting technological change and causing challenges for established firms (Henderson & Clark, 1990; Bower & Christensen, 1995). It is commonly defined as an initial inferior technology that encroaches the low-end segment of the market, diffuses up-market, and eventually grow to dominate an industry, showing to examples of the notebook computer and television challenging traditional mainframes and radios (Bower & Christensen, 1995; Christensen, 1997).

The challenges of disruptive innovations are best understood by looking at the usual trajectory of incumbents, who tend to focus their efforts on improving existing offerings in an incremental fashion (i.e., sustaining innovations). While this strategy is likely to meet the demands of the mainstream market and their most demanding customers, it may exceed the needs of the low-end market. In effect, new entrants would be better positioned to capture market shares among those who were over-served by current offerings. This is illustrated in Figure 5, which shows that whenever incumbents continue on their sustaining trajectory, new entrants will be able to capture the low-end market segment, and move up-market. Eventually, these new products or services will improve (i.e., through incremental improvements) to such an extent that they also satisfy the needs of the mainstream and high-end market, thus replacing established firms and their offerings. Whenever such a displacement occurs, the innovation is defined as being disruptive (Christensen et al., 2015). Consequently, the motivation of entrepreneurs to pursue such innovations should be urgent, as "... disruptive technologies tend to be associated with the replacement of incumbents by entrants" (Danneels, 2004, p. 247). However, until this tipping point occurs, it it hard to tell if an innovation is just radical (i.e., providing a significant technological development) or truly disruptive.

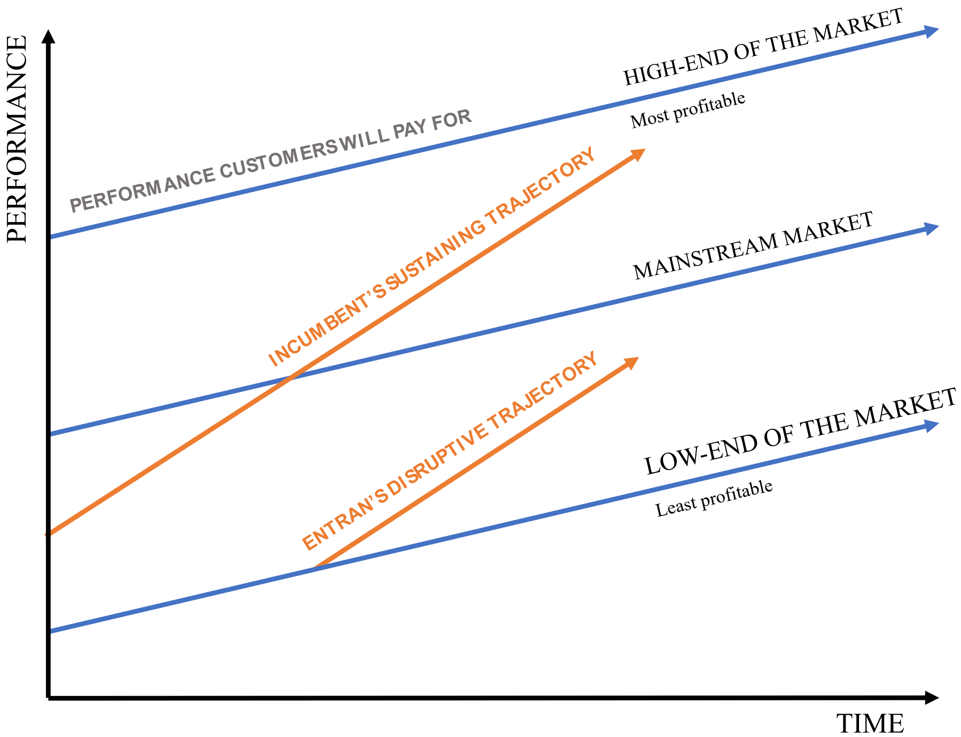

Figure 5: The impact of sustaining and disruptive technology (adapted from Christensen, 1997)

The market dynamics of sustaining versus disruptive innovations further led to the conceptualization of the *Innovator's dilemma* (Christensen, 1997). With a focus on new technologies and products, he illustrates the dilemma faced by incumbents when new and potentially disruptive technologies are introduced. On one hand, incumbents can frame the new technologies as an unlikely threat, thus choosing to continue satisfying (and potentially exceeding) the needs of their current customers through sustaining innovations. On the other hand, incumbents can adopt new technologies in an attempt to reduce or eliminate the disruptive threat. However, deciding to dedicate valuable resources to a niche and unproven opportunity is risky, and can lead to lower short-term profitability, and is no guarantee for future success (Christensen, 1997). Consequently, even though these technologies do not immediately appear to address customer needs, the outcome could become fatal when two (i.e., incumbents and new entrants) paradigmatic trajectories of progress interact.

Examples of disruption exist across a wide range of industries, illustrating a consistent pattern where leading companies fail to stay at the top of their industries (Bower & Christensen, 1995). For instance, while camera phones started out with poor capabilities, they eventually displaced many consumers' need for digital cameras. With the introduction of Wikipedia, other encyclopedias practically became worthless, and within the media industry, Netflix have basically driven traditional video rentals to bankruptcy. These examples illustrate how the theory has proven its significance, thus stressing the importance of understanding, and adapting to, an ever-changing threat of disruption. Disruptive innovation imply the end of industries as we know them (Christensen, 1997, Foster & Kaplan, 2011), and is consequently a major source of competitive advantage for those who master it (Christensen, 2001; Thomond, Herzberg & Lettice, 2003).

3.1.2 Classifying Different Forms of Disruptive Innovations

Markides (2006) argues that a generalization of the term disruptive innovations is inadequate, as different innovations propose unique types of challenges. This called for a classification of disruptive innovations, setting the foundation for analyzing strategic approaches through various lenses, based on *Innovation Type* and *Market Diffusion* (Christensen & Raynor, 2003; Govindarajan & Kopalle; 2006). Furthemore, such a distinction is not only important when trying to recognize or adapt to disruptive innovations, but also critical for identifying innovations that are *not* disruptive.

Disruption was initially introduced as a technology phenomenon (Bower & Christensen, 1995). However, the theoretical implications were quickly extended to apply other innovations types, such as services and business models (Christensen & Raynor, 2003). As Andy Grove (as cited in Chesbrough, 2010), former CEO of Intel said: "Disruptive technologies is a misnomer. What it is, is trivial technology that screws up your business model." Building on the work of Christensen & Raynor (2003), Markides (2006) argued that disruption can occur through three different types of innovations: (1) with *technology innovations* (i.e., as described by Christensen, 1997, see Section 3.1.1), (2) with *radical product innovation*, and (3) with *business model innovation.* However, as blockchain based home-sharing platforms offers a service (e.g., by allowing transacting peers to connect), the concept of radical product innovation seems unfit to describe the phenomena. However, since scholars widely acknowledge disruption as primarily a business model problem (e.g., Christensen, 2006; Lindgardt et al., 2009), the following sections will be focused around business model innovation.

A business model is said to be disruptive if it is fundamentally different from the business model in the existing business. These innovations redefine what an existing product or service is, and how it is provided to the customer. Examples of firms that were able to succeed with business model innovation is how Amazon challenged bookstores by providing sales online, the way Airbnb changed the accommodation industry and how Swatch redefined the watch industry

(Christensen & Raynor, 2003; Markides, 2006). However, in order to fulfill the requirements of business model disruption, the business model innovation must enlarge the existing economic pie, either by attracting new customers or encouraging existing consumers to consume more. Moreover, Chesbrough (2010) argue that what essentially disrupts incumbent firms is not their inability to conceive of the disruptive technology. Instead, he points to the dilemma between established business models and the exploitation of disruptive technologies; as the incumbents have committed substantial resources to succeed in already established markets with high profit margins, their motivations to pursue disruptive innovations are low, as it may cannibalize their revenues.

Traditionally, disruptive innovations have been portrayed as low-price products or services with poorer capabilities that are initially introduced to the low-end segment, before gradually paving its way up-market and wiping out the established players (Christensen, 1997). However, is soon became clear that not every disruptive innovation followed along this path. The iPhone, for example, was introduced to the market with a price that exceeded the incumbents price offerings (Gans, 2015). Consequently, the framework of disruption has later been adapted to encompass a broader view of disruption. While these divisions have not gained the same acceptance, academic literature acknowledges the existence of *new-market disruptions* and *high-end disruptions* as additional market diffusion trajectories. New market disruptions take hold in completely new markets, turning previous non-consumers into consumers, exemplified by how the introduction of personal computers made a completely new market for communication (Christensen & Raynor, 2003; Henderson, 2006). High-end disruptions, on the other hand, enter the market by offering radical and expensive technologies, serving the high-end customers, before moving down-market as affordability improves, and eventually overtaking the entire market. Examples of such innovations includes the Ipod, smartphones and light bulbs (Govindarajan & Kopalle, 2006).

3.1.3 Entrants' Way to Disruption

As mentioned in Chapter 1, literature on innovation shows that radical innovations are often developed and commercialized by new entrants (Christensen & Bower, 1996; Henderson & Clark, 1990; Tushman & Anderson, 1986; Teece, 2017). Furthermore, the work of Yu and Hang (2010) strengthen this theory, arguing that entrants are better suited for disruptive innovative success than incumbents, due to their smaller size, shorter history and less commitment to value networks and current technological paradigms. Hitt, Ireland, Camp and Sexton (2001) state that entrepreneurs are often interested in finding fundamentally new ways of doing business, and Christensen, Johnson and Rigby (2002) propose that companies wanting to create new growth businesses should seek disruptive opportunities. This is because industry leaders are not motivated to pursue them, and the probability of creating a successful new growth business is ten times greater if the innovators pursue a disruptive strategy. In such, Christensen et al., (2002) also developed two general strategies for turning ideas into plans for disruptive growth businesses:

1. Businesses seeking disruptive growth through the creation of new markets should first search for ways to compete against non-consumption, as it is considered easier to target potential new customers. Moreover, their strategies should meet the following three litmus tests:

Test 1: Does the innovation target customers who in the past have not been able to "do it themselves" for lack of money or skills?

Test 2: Is the innovation aimed at customers who will welcome a simple product?

Test 3: Will the innovation help customers do more easily and effectively what they are already trying to do?

2. Businesses seeking disruptive growth through low-end disruption of prevailing business models should first target the least-demanding tiers of the market. Next, the innovation must be made and marketed within a disruptive business model, one that enables profitability while still being price-competitive. Their strategy must meet conform to the following litmus tests:

Test 1: Are prevailing products more than good enough?

Test 2: Can you create a different business model?

However, besides Christensen et al.'s (2002) strategic outline, most of the existing literature emphasize on how incumbent firms can overcome disruptive innovation, and provides a general useful warning about managerial myopia (King & Baatartogtokh, 2015). Hence, we agree with Thomond, Herzberg & Lettice (2003), who argue that there exists an academic gap on literature with a pragmatic comprehension of how firms can understand and foster disruptive innovation as part of a major competitive strategy. Despite this, while most literature presents characteristics of disruptive innovations with the purpose of helping established players recognize its development, it also gives insights to attributes of successful disruption. Hence, based on some of the most acknowledged theories on disruption (Christensen, 1997; Christensen & Bower, 1996; Christensen & Raynor, 2003; Govindarajan & Kopalle, 2006; Henderson, 2006), we present five key characteristics for disruptive innovations:

1. The innovation is either a radical new technology breakthrough or a fundamentally new business model relative to existing offerings.
2. The innovation either starts by underperforming (low-end disruption) or overperforming (high-end disruption) mainstream attributes valued by the customers, or penetrate completely new markets (new-market disruption).
3. The attributes of the innovation is not initially valued by the mainstream customer market.
4. The innovation is either simpler, more convenient and cheaper (low-end disruption) or radical and more expensive (high-end disruption) than existing offerings.
5. Over time, sustaining innovations improve the disruptive offering's performance (low-end/new-market disruption) or affordability (high-end disruption) to a level where the innovation begins to attract the mainstream market.

3.2 The Role of Trust in Home-Sharing

The concept of sharing is as old as the history of human existence, and has laid the foundation for one of the oldest forms of social and economic empowerment. Alongside technological advancements in the 20th and 21st century, the sharing economy has emerged as a new technological business model, fueled by developments in information and communication technology, growing consumer awareness, social commerce, proliferation of collaborative web communities (Sundararajan, 2014; Botsman & Rogers, 2010; Kaplan & Haenlein, 2010; Wang & Zhang, 2012), and sustainability concerns (Lovins & Cohen, 2011; Stead & Stead, 2013).

As introduced in our conceptual model in Section 1.3, trust is a key component for the establishment of successful collaborative environments. With blockchain technology, we are provided with entirely new ways of establishing trust in peer-to-peer communities. This will have a great impact on the sharing economy, because trusted intermediaries can be replaced by trust in computational code and networking consensus (Swan, 2015). As the founder of Ethereum, Vitalik Buterin puts it: "Whereas most technologies tend to automate workers on the periphery doing menial tasks, blockchains automate away the center. Instead of putting the taxi driver out of a job, blockchain puts Uber out of a job and lets the taxi drivers work with the customer directly (Tapscott, 2016)."

There exists extensive literature on the subject of trust and trust mechanisms in online peer-to-peer platforms (e.g., Mittendorf, 2017; Ert, Fleischer, & Magen, 2016; Zheng, Li & Hou, 2011). However, these transactions have historically been enabled by the presence of trustworthy intermediaries (Hong & Cho, 2011; Wallenstein & Shelat, 2017; Mittendorf, 2017). Consequently, if blockchain-based sharing platforms aims to reach mainstream adoption, the familiar notion of institutional trust needs to be overcome, and replaced by other trust mechanisms. In 2017, Rachel Botsman, a recognized trust expert, published a book called *Who Can You Trust? How Technology Brought Us Together and Why It Might Drive Us Apart*. In this publication she sheds light on the trust crisis unraveling in our society, arguing that the major waves of disruption and change in individuals and society can be understood by exploring the evolution of trust.

Throughout history, trust has evolved in three significant steps: *local*, *institutional* and into the phase we are now entering, *distributed* (see Figure 6). Blockchain technology presents opportunities to build platforms where users do not need to trust other users in the network, just the network itself (Dapp & Karollus 2015; Swan, 2015; p.2). Many are recognizing the power of the blockchain to act as a new kind of digital trust broker. However, people still have to establish trust in the technology in order for new blockchain-based entrepreneurial ideas to commercialize.

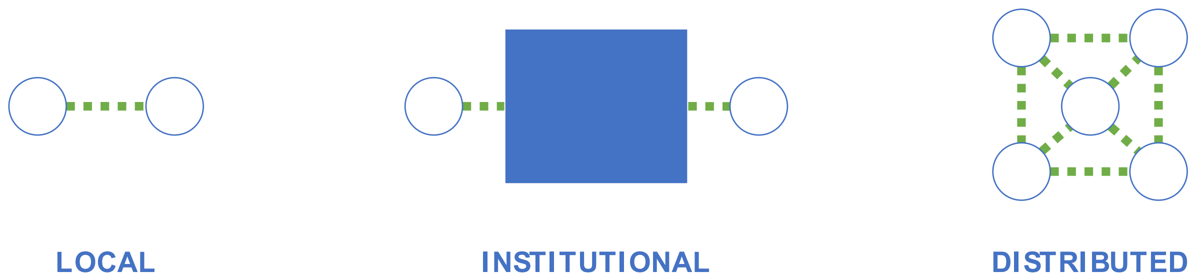

Figure 6: The evolution of trust (adopted from Botsman, 2016)

3.2.1 Defining Trust

According to Eisenegger (2009), trust is the most important operational resource in our society. However, trust is a complex concept, and developing an accurate definition of trust is challenging due to the vast applicability the term has in everyday life (McKnight & Chervany, 2001). Additionally, researchers from different disciplines approach the term from various angles (Lewicki & Bunker, 1995). Hence, a coherent and satisfactory definition of the term does not exist (Taddeo, 2009; Hosmer, 1995; Taylor, 1989). While Gambetta (2000) define it as "a particular level of the subjective probability with which an agent assesses that another agent (or group of agents) will perform a particular action, both before he can monitor such action (...) and in a context in which it affects his own action (p. 216)", a more generic formulation is given by Luhmann (2018) as "the confidence in one's expectations (p. 5)".

3.2.2 The History of Trust

From Local to Institutional Trust

Up until the mid-1800s, way before our internet-connected world emerged, trust was built mainly around established social relationships, and was primarily local and accountability-based (Botsman, 2016). During this period, the main source of income and assets came from exchanging local goods and services. Thus, being untrustworthy or dishonest within a small community would result in a bad reputation. As we entered the 20th century, people started moving into larger cities, and the familiarity of social exchanges was replaced by institutional exchanges; you no longer knew your local banker, and people were forced to adapt to interactions with larger corporations. Alongside this tremendous societal change, we entered a new trust chapter. Personal reputation and accountability was replaced by other trust mechanisms, including contracts, regulations and insurances. This led to the establishment of *institutional trust* (Botsman, 2017).

The Lack of Trust in Institutions

Historically, centralized organizations and institutional banks have been considered crucial for economic growth by facilitating employment, technological innovations and infrastructure development (Acemoglu & Robinson, 2008). However, after the man-made financial crisis of 2008, trust in centralized and institutional systems decreased considerably (Earle, 2009). Ever since the Watergate scandal and the Vietnam War in the 1970s, Gallup have surveyed Americans regarding their confidence in major institutions. This survey reveals that trust in institutions has severely declined since the first survey was deployed in 1973. For example, the percentage that had *great* or *quite a lot* of confidence in big businesses in 1975 decreased from 34 percent to 21 percent in 2017 (Gallup, 2017a). As for banks, the reduction is even more significant, dropping from 60 to 32 percent over the same period. Moreover, interesting results from another empirical study conducted by Sapienza and Zingales (2012), revealed a shift in trust tendencies after the financial crisis; people now put notably more trust in strangers than they do in official institutions. According to the Economist Intelligence Unit (2017), both Brexit and the presidential election of Donald Trump are symptoms of the ongoing shift in trust, as both represent the movement in which trust and influence is no longer given to the institutions and the elites, but rather lies in the hands of the people.

Eisenegger (2009) argues that we are underestimating the impact of the financial crisis by only looking at it from an economic perspective. The recession has not only harmed the stock market, but also resulted in numerous corporate collapses, and even bankruptcy of entire national economies. In essence, the crisis had impact far beyond the economic recession, damaging the trustworthiness and reputation of the entire governmental economic system. Moreover, considering other scandals such as the Panama papers, Enron and Arthur Andersen, the Edward Snowden's leaks of the NSA files, the Volkswagen emission scandal, and the recent Cambridge Analytica privacy scandal, it comes as no surprise that trust in institutions have suffered major setbacks. As Mark Carney, governor of the Bank of England, said: "The succession of scandals means it is simply untenable now to argue that the problem is one of a few bad apples. The issue is with the barrels in which they are stored (Ahmed, 2014)." If you cannot trust the institutions that constitute the solid cornerstones of most economies, then who can you trust?

Distributed Trust Replacing Institutional Trust in the Sharing Economy

The combination of a massive social media expansion in the first two decades of the 21st century, the networking power of the Internet, the financial recession, and the lack of institutional trust sowed the seeds for the sharing economy (Munoz & Cohen, 2017). Consumers were looking for new ways to lower their daily expenses, laborers were looking for new sources of income, and the Internet provided them with new ways to interact with each other. Consequently, several initiatives for alternative deployment of unused assets and schemes for offering idle capacity proliferated within the sharing economy (Schor, 2016; Schor & Fitzmaurice, 2015). And as previously mentioned, establishing trust between peers engaging in sharing activities is crucial in order for the success of any sharing initiative. Botsman (2017) even refers to trust as the currency of the sharing economy, and Gebbia (2016) argues that the 'stranger-danger-bias' is the main barrier for the growth of the sharing economy, as people commonly view transacting with strangers as a source of increased probability of danger.

As the sharing economy involves exchanges between strangers, there is no previous history that allows the peers to assess each other's trustworthiness. The sharing economy has resolved this by designing digital reviews and feedback systems (Weber, 2014), allowing strangers to rely on the subjective experiences of others. According to Friedman (2008), reputational enforcement works because it makes information about bad behavior accessible. To further enhance the legitimacy (and in effect the trustworthiness) of users, sharing platforms often demand users to validate different information metrics on their profiles, ranging from verification of identification papers, email addresses, phone numbers, personal photos or social media accounts (e.g., Facebook). The accumulation of reviews, alongside the validation of personal attributes and information enables peers to build a reputational profile. Hence, reputation through online interactions allows for the modern notion of trust in institutions to be replaced with trust in strangers. Consequently, the trust that once flew upwards, to regulators, institutions and authorities, now flows sideways, peer-to-peer, through social networks and online market platforms (Botsman, 2016). Botsman (2016) argues that at the macro level, what ultimately facilitates the sharing economy is a shift in our trust orientation, into the new era of distributed trust.

Today, AirBnb is valued at more than $30 billion, and more than 260 million stays have been completed through the platform (Molla, 2017). This illustrates how far, rapid and peripheral we are willing to extend our trust just because technology provides us with a filter. Despite the success of Airbnb, one in three consumers reported that they had experienced a problem with an item or service through peer-to-peer marketplaces (OECD, 2017). Hence, challenges that hampers an age of truly distributed trust still exist. This also makes ”over-trusting” a critical source of complication in the sharing economy (Botsman, 2017). Take for example the incident where a nineteen-year-old boy was sexually assaulted by his host during an Airbnb stay in Madrid (Lieber, 2015). Or the case where an Uber driver in Michigan committed six unprovoked random murders, whilst at the same time picking up people through the Uber app (Botsman, 2017). One of his passengers (who lived to tell the tale) even prompted to the driver: “You are not the shooter, are you?”, but still decided to stay in the car.

Hence, it becomes evident that there are great amounts of risk involved as we move towards an era of distributed trust. As Botsman (2017, p. 65) puts it: “Its potential is massive but there’s a catch. While distributed trust may sound like a techno-libertarian dream, the flip side is that the same tools that are being used to connect strangers all over the world can also be used in deeply unsettling and nefarious ways.” While it is still in its early days, distributed trust has powered the rise of multi-billion-dollar companies like Airbnb and Uber. However, Arun Sundararajan, a renowned economist and sharing economy expert, argue that (as cited in Kane, 2016): “(…) getting into a stranger’s car and asking to be driven to another city, or letting someone you don’t know sleep in your spare bedroom — the stakes are a lot higher, so the level of trust also needs to be a lot higher in order to make this kind of activity viable at scale (p. 129).”

3.2.3 The Power Discrepancy in The Sharing Economy

As introduced in Chapter 1, the sharing economy has shifted the traditional notion of competitive advantage in several sectors. Nevertheless, the creators of the shared content (i.e., the micro-entrepreneurs) are often obligated to distribute much of their earnings to the intermediary proprietors (De Filippi, 2015). For instance, as of April 2018, Airbnb is charging guest services fees up to 20 percent, in addition to demanding close to 3 percent of the hosts’ commission (Airbnb, n.d.a). Hence, the platform revolution following Airbnb and other sharing initiatives is seemingly focused on enriching the platform owners at the expense of the value creators (Tasca & Ulieru, 2016).

Moreover, Hira and Reilly (2017) highlight an additional concern with regards to the lack of competition faced by many platform giants, illustrating why Uber has been able to raise its commission fees to 30 percent in the Swiss market. Due to their positive networking effects, and the lack of competitive alternatives, platforms like Uber or Airbnb have almost achieved a monopolistic stance within their sector of sharing service. As they put it: “The low marginal costs of entry should mean a highly competitive marketplace, yet thus far first to market seems to be the prevailing source of concentrated advantage. This mirrors what we see in most parts of the internet economy — the dominance of Google, Microsoft, Apple, Facebook, and Amazon in their respective sub-sectors (Hira & Reilly, 2017, p. 180)”.

As mentioned in Chapter 1, the position of the intermediaries in the sharing economy is questionable; can sharing through a profit-maximizing intermediary be considered “true sharing”? However, as strangers are unable to complete direct sharing transactions due to the presence of high transaction cost and agency problems (see Jensen & Meckling, 1976; Eisenhardt, 1989 for agency theory and Coase, 1973; Williamson, 1979; 1981 for transaction cost theory), the platform bring a lot of value to the exchanges. In turn, this allows the platforms to capture a lot of the value made through these exchanges. In Pazaitis, Kostakis and Bauwens (2017), this power discrepancy between intermediaries and microentrepreneurs is addressed. The power discrepancy has been the source of substantial criticism towards sharing economy platforms. As Scholz (2016, p. 1) puts is: “The current owners of online platforms are willing to offer us seemingly everything except ownership. It is time for us to instead create an online economy based in democracy and solidarity.” The sharpest critics even go as far as calling the platforms nothing more than capitalistic technology giants in disguise (Killick, 2015), and describes the development as “something worse than capitalism” (Wark, 2014). As Benkler argue in Tapscott and Tapscott (2016, p. 157): “It’s nonsense to call Uber a sharing economy company, (...) Uber has used the availability of mobile technology to create a business that lowers the cost of transportation for consumers. That’s all it has done.” However, most of us are raised to not trust strangers, and thus it is expensive, time consuming and risky for individuals to perform sharing exchanges independent of a trusted third-party.

3.3 Blockchain Attributes Perspectives

To understand the disruptive potential of blockchain technology in home-sharing, it is important to first obtain an understanding of its technological features. When Nakamoto published the Bitcoin software in 2009, he seemed to be aware of the widespread possibilities of his invention. In 2010, he stated that “the design supports a tremendous variety of possible transaction types that I designed years ago. Escrow transactions, bonded contracts, third-party arbitration, multiparty signature, etc. If Bitcoin catches on in a big way, these are things we’ll want to explore in the future, but they all had to be designed at the beginning to make sure they would be possible later.” Consequently, this chapter will provide insight to some of the key attributes of blockchain technology, with application areas in home-sharing. These include (1) security, (2) privacy protection, (3) transparency, and (4) reputation management.

3.3.1 Security

Improved Payment Systems

Blockchain technology has received substantial attention within the financial industry, being referred to as potentially the most promising technology in financial services ever (e.g., Buehler et al., 2015; Courtneidge & Buelli, 2015; Taylor, 2015). Also Nakamoto's (2008) grand vision was initially limited to money transfers. While he clearly was aware of his invention's potential, his original work did not include any discussions on business model disruption, an era of renewed trust or a transformation of the cornerstones in which society is built upon. The use of blockchain technology was at first a core breakthrough in computer science due to its ability to solve the long-standing *double-spending problem* without the dependence of a third party. The issue of double spending has traditionally hampered the developments of electronic currencies because digital information is relatively easy to reproduce, which in turn allows for users to "spend the same money" twice (Pointcheval & Stern, 2000).

The issue of double spending clearly illustrates the need for intermediating services (e.g., banks, Paypal or Visa) when individuals want to transact online. By solving this double-spending problem, Nakamoto (2008) enabled a peer-to-peer electronic system for money transfer, which in turn eliminates the need for such intermediaries. And with this, Nakamoto also made transaction between individuals available in a completely decentralized, distributed, and global way. In a very simplified manner, a transaction of Bitcoins would occur like this: Alice wants to transfer 1 bitcoin to another peer in the network, Bob. The first thing Alice needs to do is to broadcast the message "send 1 bitcoin from Alice to Bob" to the network. To verify that Alice actually is who she says and that Alice have the amount of bitcoin available, the network has implemented a digital signing scheme. Almost like the password required to log on to your email, every peer in the bitcoin network has a private key connected to their public key, which is utilized to make digital signatures verifying users. Hence, to spend money belonging to an account in the bitcoin network, both a private and a public key is needed. Consequently, as only you have access to your private key (unless you write it down or store it somewhere unsafe), your money will remain safe in your cryptocurrency wallet[7]. Additionally, users are able to store their funds in a *cold storage wallet,* meaning that users are able to store their cryptocurrencies offline (Apodaca, 2017). By doing so, the funds are not present on any server or computer, which reduces any potential hackers to steal your assets.

The use of cryptocurrencies make sense from both an economic and security perspective, and according to Swan (2015), blockchain is already becoming the cash for the Internet, and could in the future become "The Internet of Money". As noted, the core functionality of cryptocurrencies is that any transaction (money or other intangible assets) can be completed

[7]A cryptocurrency wallet is a software program that stores private and public keys and interacts with various blockchains to enable users to send and receive digital currency (Rosic, 2017).

peer-to-peer. In effect, credit card merchant fees may reduce from as much as 3 percent (or even 7-30 percent in remittances markets) to below 1 percent. Moreover, while payments through financial third-parties could in some events take days, or even weeks, to settle, cryptocurrencies move instantly from the sender to the receiver's digital cryptocurrency wallet (Swan, 2015). The core functionality of blockchain is that any participant in the network can allocate and transfer funds domestically and internationally in a more efficient, cost-reducing, safe and distributed way. In such, blockchain and cryptocurrency solves previous challenges with transaction fees, poor foreign exchange rates, and slow and cumbersome process available through traditional cross-border payment services (Hileman, 2015), eliminate inefficiencies by making transactions faster and at a lower cost, while also providing increased liquidity, transparency and security (Manuel & Andrews, 2016), minimize the need for intermediary, thus increasing speed, and reducing costs and risk of fraud (Norton, 2016).

Asset Safety and Trustless Lending

The concept of smart properties was investigated in our preceding project thesis (Boge & Nyrønning, 2017), and relates to how blockchain technology can be used to register and transfer assets through smart contracting. When ownership of any property is encrypted into a blockchain, it becomes a "smart property" or "smart asset", which can be tracked, controlled and exchanged on the blockchain ledger (Swan, 2015). This also means that the smart asset has access to the blockchain, and is able to read information from the blockchain and perform activities through the terms encrypted in a smart contract (Franco, 2014). The smart properties are controlled by the ones entitled to the private key, and changes of ownership happens by transferring the private key to another party. In the home-sharing environment, this feature will allow guest and hosts to engage in *trustless lending.* The following example illustrate several use-cases for smart contracting through smart properties in home-sharing.

Consider the following scenario: Bob is searching for an apartment in New York on a blockchain based home-sharing platform, and decides to send a booking request to Alice. They are then connected through the platform, and can discuss the terms that should be included in the smart contract governing the tenancy. As Bob has high demands for quality of the apartment, he wants to inspect the apartment in-person before he agrees to stay at her place. Alice agrees to this, but demands that if he chooses to not stay at the apartment, 20 percent of the pre-allocated cryptocurrency will be transferred to her crypto wallet. Alice, on the other hand, requires a $200 deposit which will be at her disposal in the event of any misconduct or theft from Bob.

When Bob arrives to the apartment he simply displays an electronic ticket (a QR-code) that Alice can scan to initiate the booking. As of now, the smart contract will automatically transfer the temporary ownership to Bob. Alice has integrated her Wi-Fi and air condition on the blockchain as a smart property, which means that the contract can incorporate usage of the respective services. Consequently, if Bob wants to have internet access or cool down the apartment during his stay, he just needs to pay for their private keys. In the event that the internet connection is slow, he may even return the private key and only pay for the amount he has used, as the contract states that he will only be charged for the period of access. Figure 7 illustrates the basic coding that can be implemented in a smart contract for renting on the Ethereum blockchain.

**An Ethereum smart contract to rent out apartment in March for 50 ether

**First, the renter's Ethereum address:

8ah5679499dfgq5896kl773 into smart contracts "storage" as RENTER

**Then apartment owner's address:

9ch5641499etlk9816kl113 in smart contracts "storage" as OWNER

**March 1, 2018 is 19838463729 is "renting start"

19838463729 in smart contracts "storage" as DEADLINE

**March 31, 2018 is 39196463449 is "renting stop"

39196463449 in smart contracts "storage" as MOVING DAY

**If the agreed amount is received on time...

When (transaction value >= 50 ether) and (block timestamp <= storage DEADLINE)

** … then designate the renter as the temporary owner of the apartment for the given period and pay the current owner

Then (put storage RENTER in storage TEMPORARY_OWNER) and (spend contract balance to storage OWNER)

If (daystamp > storage MOVINGDAY) Then (put storage OWNER) in storage TEMPORARY_OWNER)

Figure 7: Illustration of a smart contract for renting on Ethereum

The above example shows how blockchain and smart contracts provide the extra security needed to trustfully trade smart property and assets without the perception of potential risk. It also illustrates how the contractual preconditions, as well as rules of behaviour could easily be implemented in a rental agreement. This holds great promise for reducing contract disputations and litigations, as the contracts and assets involved are being settled automatically by coding enforcement mechanisms. Hence, it becomes evident just how useful smart contracts could be to minimize enforcement costs, as well as prevent moral hazards and adverse selection (Shermin, 2017). What a smart contract essentially could do through the blockchain is to codify the rules and decision making apparatus of an app (make a DApp), so that we can trust the code instead of the current intermediaries (Swan, 2015).

However, some issues still exist in relation to seamless execution of transactions through a smart contract. Blockchains are only able to see the activity occurring inside their network, restricting them from implementing outcomes from the real world. To cope with this, blockchains get input from information sources such as web pages or sensors. This external source is referred to as an *oracle* (von Kohorn, 2018). This oracle will control the input to the smart contract, which in effect means that it also holds the power to determine what the smart contract does in response to different inputs (Delphi, 2017). Consequently, even if the smart contract underpinning an agreement is reliable, the reliability of the external source will remain questionable. Just consider the case where Bob would be granted free access to Alice's air condition if the temperature in New York exceeded 30 degrees Celsius upon arrival. The smart contract would then collect information regarding the temperature, and allow Bob to use the air condition without having to pay for the private keys if the temperature exceeds 30 degrees. However, if the external temperature oracle provides the smart contract with corrupted information (e.g., supplying the contract with information that states 32 degrees, when it in reality is 29 degrees), the access will be granted falsely. With no further possibilities to reverse transactions on the immutable ledger, the outcome of the contract is thus final (Jacobs, 2018), and Alice will lose the potential revenues from Bob's air conditioner usage.

Hence, a smart contract is not sufficient to regulate such relationships; you need a smart contract plus a reliable oracle (Delphi, 2017). To mitigate the risk associated with oracles, smart contracts could be programmed to check several sources, and only execute after at least two of three has given the same result (Tapscott & Tapscott, 2016). Another obstacle in depending on oracles in the contracts is the availability of the oracles, as well as the delivery of the same information to all nodes of the decentralized blockchain network.

3.3.2 Privacy Protection

Privacy is considered a core human right in free societies, and according to Tapscott and Tapscott (2016), everyone should be able to control their own data, including *what*, *when*, *how* and *how much* of their identities they wish to share with another party. And as of today, consumers view the privacy and security of their personal data as important (Zyskind, Nathan & Pentland, 2015). However, most people are unaware of how their personal data is utilized, as they only scan "the small print" of the terms and conditions (OECD, 2017). Consequently, by agreeing to these conditions, users also allow technology platforms to collect and scrutinize personal data, either to harvest in their own interests, or to understand our lives and desires to better predict our future actions and behaviors (Korosec, 2018). Nevertheless, giving up data has become part of the trade-off of receiving compelling, price-competitive and personalized services. In effect, vast amounts of personal data is stored in a centralized server that is potential open to manipulation, attacks or damages (Sheedy, 2018).

With blockchain technology, the risk associated with privacy concerns are greatly reduced due to the two following reasons: (1) the system allows users to trust each other without knowing the true identities, which greatly reduces the information you have to provide to complete the transaction (Tapscott & Tapscott, 2016) and (2) the technology enables us to eliminate the need of third-parties, which in turn eliminates the centralization of data. Through transactions on the blockchain, personal details are only shared amongst participants involved in the transactions. This also means that no proprietary owner (e.g., intermediary) have access or rights to information about the networking users. As Tapscott and Tapscott (2016) neatly put it: "there are no honeypots of data on the blockchain", which in turn reduces the ability for any entity to monitor your data.

Moreover, a blockchain does not need to know who its users or nodes are, and participants are not obligated to provide personal data in order to access the (public) blockchain. In effect participants can maintain an anonymous profile, which makes it virtually impossible to connect actions to identities (i.e., you have to do a considerable amount of triangulation of data to figure out who or what owns a particular public key) (Catalini & Gans, 2016). In addition, users can deploy several techniques to protect their sensitive data: (1) they can use a new address for each transaction, thus obfuscate their transactions by mixing them with others, (2) use a completely anonymous cryptocurrency in payments, (3) rely on an intermediary like a digital wallet provider or (4) use a system that separates basic information about a transaction (e.g., its existence and timestamp) from more sensitive information. In relation to the latter technique, the personal data could instead be stored on a private blockchain (or database) linked to the public blockchain by cryptographic algorithms (Catalini & Gans, 2016).

For businesses realizing how data storage is becoming a source of consumer criticism, blockchain present an opportunity for them to reduce their data liability. For example, systems can be implemented such that users control their own data, but they may delegate permissions to the company that wishes to access the information. This leaves users with full transparency on what, when and how data that is being collected (Zyskind et al., 2015), and in turn allows users to choose the level of privacy they are comfortable with.

3.3.3 Transparency

As introduced in Section 3.2.2, trust in centralized institutions has experienced a significant drop since the 1970s. In the wake of several frauds in the turn of the 21th century (e.g., how Enron used accounting tricks to pump up its share price, or how Xerox admitted to overstating its revenues by almost $2 billion over a five-year period) (Pratley & Treanor, 2002), Tapscott and Tiscoll (2003) argued that corporations are better served with being transparent and honest. They further label transparency as a new form of power that is becoming central to the success of businesses. With blockchain technology, transparency is the norm, rather than the exception; all transactions in the networks can be tracked and are impossible to alter on the tamper-proof ledger (Piekarska, 2018). Hence, this will allow for clear transparency and auditability for companies and their stakeholders. And since the data can be transferred anonymously, the information navigates through the network without breaching confidentiality (Martyn, 2018).

Even though Nakamoto was the creator(s) of the Bitcoin software in 2009, it was labelled as *open source* (Jacobs, 2011), meaning that no entity (e.g., company or government) controls or owns the code. Consequently, in the years following the initial release of the code, the "Bitcoin wave" spread across the Internet community, and programmers all over the world collaborated with further developments of the software (Southurst, 2018). All records related to the use of Bitcoin are open to public viewing, which means that the protocol keeps track of every move in the network (Piekarska, 2018). In effect, this means that there is nowhere to hide fraudulent actions on the network (Mauri, 2017). By using an explorer (i.e., an online chain browser), users can view the content of each individual block, including the size of the block, the amounts being transferred, when it was transferred, and what addresses it was sent from (Bruno, 2017). An example of such a browser is the Bitcoin Explorer (available at Blockchyper.com).

Even though most of the activity on the blockchain is currently centered around financial transactions, there exist a vast amount of other assets (both tangible and intangible) that can be registered and traded on the ledger (Swan, 2015). For example, you can put the ownership of your car on the blockchain, and if you ever want to sell it, all you have to do is to digitally transfer the ownership to the buyer. This can be performed without any paperwork - just hand over the keys and transfer the digital assets that are currently representing the car. Consequently, the history of the car is stored on the blockchain, which provides any future buyer with a true picture of who the car has belonged to, how old it is and what price it was sold for. This is applicable to a vast selection of other assets as well, which in turn proves how the blockchain can provide transparency. However, this might seem contrary to the attribute of privacy introduced in section 3.3.2; How can blockchain provide transparency and privacy at the same time? The key difference lies in the fact that the sensitive transaction details are only shared amongst the participants involved in the specific transaction (through private keys that decrypts the data), whereas the transaction itself (e.g., its timestamp and amount transferred) is visible to the network (Myler, 2017).

3.3.4 Reputation Management

As introduced earlier, review and feedback mechanisms are key to establishing trust between peers interacting through a sharing-service platform. However, even though this is a necessity for sharing platforms to function, it also allows for data giants, such as Airbnb, to control and access the reviews. Additionally, as the reputation data is owned by Airbnb, it can not be transferred to other platforms (Cartagena, 2014). Consequently, if you have listed you apartment on both Airbnb and Homeaway (a similar home-sharing platform), you would not be able to leverage your previous reputation, which in turn forces you to build your reputation as a host from scratch. In a TED talk from 2012, Botsman envisioned a future where the reviews and feedbacks from different sharing platforms could be accumulated into a single digitized representation of yourself; where your behaviour as a guest on Airbnb, your punctuality as a babysitter on Urban Sitters, and your hospitality as an Uber driver would be represented through a single (and transferable) digital “you” (Botsman, 2012).

Some startups are already working on developing such a cross-reputational management scheme. One example is the blockchain-based startup Tru Reputation Network, which is developing a DApp aimed at establishing a reputation protocol that will allow peers to build and transfer their reputation across digital ecosystems (Bray, 2017). Just consider how transactions are validated on the blockchain ledger - through networked consensus of the participants. This mechanism is the idea behind the Tru DApp: instead of validating transactions, the DApp is going to allow peers to validate how trustworthy a transacting peer is. Consequently, this mechanism will only allow a peer to build trust if multiple decentralized entities agree that you are in fact trustworthy, and potentially eliminate the existence of fake reviews (Bray, 2017). Moreover, the accumulated reputation from the Tru network is owned by the individual users, and can be extended to any new platform or forum. Dennis and Owen (2015) present a similar reputation blockchain, where the human opinion is eliminated from the reputation assessment, and instead replaced by defining all satisfactory transactions as 1, and unsatisfactory transactions as 0. The accumulated score will then be representative for your reputation and trustworthiness.

Tapscott and Tapscott (2016) argue that the accumulated blockchain-based reputation could be leveraged in insurance schemes. Providing an illustrative example, they imagine that there exist a DApp for insurance, and a bAirbnb (i.e., a blockchain based home-sharing platform). Whenever a booking request is sent to a host, bAirbnb will automatically transfer the request to the insurance DApp. The insurance DApp will then check your reputation up against a list of trusted providers (e.g., the Tru Network DApp or other reputation platform), and calculate the insurance fee that should be added to your booking based on the market value of the house, the reputation of the host, length of the stay and the rental price. Guests with high reputation scores will then be offered lower fees, whereas guest with lower reputation scores will be subjected to higher fees. Consequently, the blockchain based reputation will allow peers to leverage their reputation to a larger extent than what is currently possible.

4 Methodology

In order to ensure the validity of our findings and enable replicability of our research approach, this chapter provides documentation on the variety of methods used in data collection and empirical studies. First, we present our overall choice of research strategy and design in Section 4.1. A review of the theoretical literature follows in Section 4.2. Thereafter, we describe our data collection methods and data material in Section 4.3, and methods of analyses performed in Excel, IBM SPSS and Stata in Section 4.4. Finally, we evaluate the quality of our research in Section 4.5.

4.1 Research Strategy and Design

While a comprehensive literature review serves as a fundamental part of addressing our research questions, our study mainly employs a quantitative research design. Consequently, following traditional quantitative research, our approach is deductive, where the purpose of exploring our data is based on our theoretical framework and research questions (Cronbach & Meehl, 1955; Bryman & Bell, 2015). The choice of a quantitative research design is in accordance with the exploratory nature of our research questions (Yin, 2009), and is thus considered suitable for examining empirical relations between measures in a population (Danial, 2004). Moreover, our research design adopts a positivist epistemological standpoint, aiming for objectivity in our data collection and statistical analysis. In addition, the research design is used to confirm our results according to the principles of validity and reliability (Becker, Bryman & Ferguson, 2012). As proposed by Bryman (2016), we followed a strategy where our research questions became more precisely defined alongside the interpretation of the data material and further exploration of the theoretical frameworks. This sequential way of working is illustrated in Figure 8.

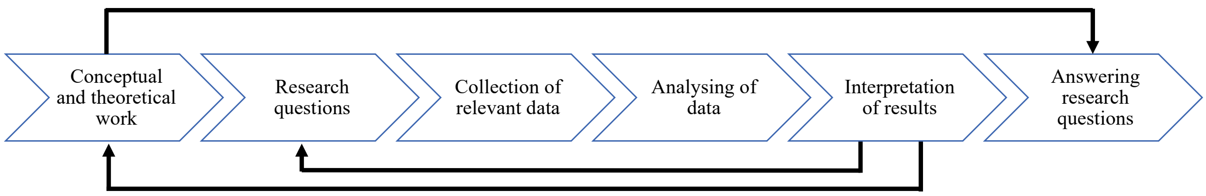

Figure 8: Quantitative deductive research design

4.2 Literature Review

A thorough review of relevant literature is the very foundation for theoretical progress, and thus essential in any academic project (Webster & Watson, 2002). Consequently, we sought to find theoretical and technical perspectives that would help us analyze and answer our research questions. As a result, our literature review focused on three main subjects: blockchain technology, disruptive innovations and trust. In order to ensure quality in the retrieved literature, we initially decided that our pool of primary literature (articles, books and papers) should fulfill three requirements: (1) it should include the most cited articles, (2) cover recent articles, papers and/or books on the subject and (3) be sourced from a credible publisher. In relation to requirement (3), we used the CiteScore percentile of the publisher, which is an indication of how well cited a journal is relative to the average within its field of research (Elsevier, n.d.). For example, a score in the 96th percentile means that the journal is ranked amongst the top 4 percent in its field. These scores are listed in the right column of Table 2, and were required to be greater than the 60th percentile to ensure the quality of the retrieved literature.

While the majority of literature fulfill the above requirements, the sharing services, blockchain technology and distributed trust are all fairly new areas of research. As a result, limited academic publications exist on the topic. Hence, in order to absorb the latest perspectives within this rapidly emerging fields of business, we have included some populistic literature and industry reports. Nevertheless, a thorough background check was required to ensure that the authors were either (1) experts within the field or (2) recognized researchers with several previous published articles. An overview of the selected primary literature is presented in Table 2.

Table 2 Selected Primary Literature

Search Terms	Selected Literature	Author(s)	Published	Source (CiteScore Percentile 2017*)
Distributed trust				
Trust and technology Botsman	Who can you trust?: How technology Brought Us Together - and Why It Could Drive Us Apart	Botsman, R.	2017	Penguin UK (N/A)
Centralized Organizations and trust	Questioning Centralized Organizations in a Time of Distributed Trust	Seidel, M. D. L.	2018	Journal of Management Inquiry (69%)
Blockchain and trust	Blockchain: Democratized trust: Distributed ledgers and the future of value	Piscini, Guastella, Rozman & Nassim	2016	Deloitte University Press (N/A)
Disruptive Innovations				
Sustaining and disruptive innovations	The innovator's dilemma: when new technologies cause great firms to fail	Christensen, C. M.	1997	Harvard Business Review (76%)
Successful growth and innovation	The Innovator's Solution: Creating and Sustaining Successful Growth.	Christensen, C. M. & Raynor, M.	2003	Harvard Business Review (76%)
Business strategy and innovation	Business models, business strategy and innovation.	Teece, D. J.	2010	Long Range Planning (99%)
Disruptive Innovations	Disruptive innovation: In need of better theory	Markides, C.	2006	Journal of product innovation management (93%)
Blockchain Technology				
Peer-to-peer Exchange	Bitcoin: A peer-to-peer electronic cash system	Nakamoto, S	2008	bitcoin.org (N/A)
Blockchain revolution	Blockchain Revolution: How the technology behind Bitcoin is changing money, business, and the world.	Tapscott, D., Tapscott, A.	2016	Penguin (N/A)
Blockchain trends	Blockchain: Blueprint for a new economy.	Swan, M.	2015	O'Reilly Media, Inc. (N/A)
Bitcoin Cryptography	Understanding Bitcoin: Cryptography, engineering and economics	Franco, P.	2014	John Wiley and Sons (N/A)

*The CiteScore Percentile is not applicable to books.

4.3 Data Material

As mentioned in Chapter 1, our data material is retrieved from two different and complementary sources: publicly available booking statistics retrieved from "Inside Airbnb" and a self-administered questionnaire. In this section, we present the data collection methods.

4.3.1 Data Triangulation

Dudovskiy (2016) states that data collection methods are divided into two categories; primary methods (i.e., data collected by the researcher himself) and secondary methods (i.e., data that has already been published in books, articles etc.). As previously mentioned, we have included both these approaches in our data collection, thus applying the concept of data triangulation. According to Creswell and Miller (2000), triangulation is "a validity procedure where researchers search for convergence among multiple and different sources of information to form themes or categories in a study (p. 126)." Moreover, Lincoln and Guba (1985) stress the importance of triangulation in research, as it allows you to assess the integrity of your conclusions by drawing from multiple sources, and thereby improving the rigor of your analysis. Hence, considering the variety in our data collection techniques, we hope our study generates a better and more coherent picture of how blockchain-based home-sharing platforms can succeed, thus reinforcing the relevance of the proposed findings.

4.3.2 Airbnb Data

Data Collection

In order to assess the market for home-sharing, we downloaded geo-located Airbnb data from "Inside Airbnb"[8]. Inside Airbnb is an independent initiative, meaning that the data is "not associated with or endorsed by Airbnb or any of Airbnb's competitors (Inside Airbnb, n.d.)." However, the data material is acknowledged as reliable within academic research, and is utilized in several recent publications (see e.g., Ma, Hancock, Mingjie & Naaman, 2017; Gurran & Phibbs, 2017; Gutiérrez, García-Palomares, Romanillos & Salas-Olmedo, 2017; Kakar, Franco, Voelz, & Wu, 2016). Consequently, we perceive the data material to be a reliable source of information.

Selection Criteria and Screening of Data

Data from Inside Airbnb's website is comprised of public information obtained from the Airbnb website, and includes location, availability, price and reviews associated with each listing. Data is available for more than 30 cities across five continents, and in order to get a coherent overview of the home-sharing market, we analyzed data from all available continents. Moreover, we selected cities with the most recent data (preferably from 2017) to ensure that our analysis most accurately represent the current home-sharing market. Thus, data was extracted from seven cities; three in North-America (Toronto, San Francisco and New York), three in Europe (Amsterdam, Barcelona and Copenhagen) and one in Australia (Sydney). For all cities, we downloaded a summary of information based on room type (entire homes/apartments; private vs shared rooms), price per night for the different room types, reviews, availability (as a fraction of 365 days) and listings per host, all measured in Desember 2016 and 2017, with the exception of Copenhagen and Toronto, where the measures stem from June/July 2016 and 2017.

With every online advertising platform, there is a possibility that listings are either outdated or "bait and switch" (i.e., offerings that upon investigation are not actually available). For instance, by exploring listings in the relevant cities through the actual Airbnb.com website, we observed that some lodging possibilities were heavily over- or underpriced. In order to limit the existence of such listings, we excluded every listing with a price above $1600 and below $16. This was done to ensure that the retrieved data represented an realistic overview of the available listings. Moreover, we excluded listings without any reviews to ensure that only active listings were included in the data set.

[8] www.insideairbnb.com

4.3.3 Survey Data

For the purpose of our study, we developed a cross-sectional survey[9]. According to Yin (2009), surveys are appropriate if the nature of the research question is a "what question", the focus of the research is on contemporary events and control of behavior events is not required. Based on the objective of our thesis, we therefore argue that such an approach is suited to answer our research questions. The upcoming section explains how our survey was designed, how we collected and screened the data, and point out limitations in the collected data set.

Survey Design

In order to reach a sufficient amount of respondents within a timeframe of two weeks, we made an electronic survey using SelectSurvey. The survey was a self-administered online questionnaire, meaning that respondents recorded his or her responses without the presence of a trained interviewer (Hair et al., 2003). The survey included a set of conditions that automatically led the respondents to follow the most appropriate path based on their experiences with sharing services. As an example, non-consumers of sharing services (i.e., respondents who answered "No" to Item 1, Appendix 2) skipped all further questions related to sharing service experiences.

The survey consisted of 24 questions[10], and was divided into four main parts. The first part of the survey was related to previous use of sharing services (home-sharing, car-sharing, sharing of household times etc.). The second part was related to evaluation of different information metrics on Airbnb hosts. In this section we used information extracted Airbnb's website regarding current available host information, and drew inspiration from the work of other scholars concerning how trust is built in sharing services. For instance, Ert, Fleischer and Magen (2016), found that guest's booking decisions on Airbnb were influenced by both listing information and personal host information. Furthermore, Öğüt and Tas (2012), found a direct, positive relationship between positive online reviews and increased revenues.

However, few scholars have looked at how other information metrics (not currently being offered on Airbnb platforms) could influence the perceived trustworthiness of hosts. Kamal and Chen (2016) have investigated this, but they limit their scope to only include access to social media accounts, criminal records and recommendations from friends. Hence, we extend their research, and include several self-developed metrics (e.g., employment record, relationship status, political orientation etc.). Hence, to better evaluate key features of a successful blockchain-based home-sharing platform, the intention with this section of questions was to reveal what information metrics (both existing and potentially new ones) were considered most valuable to get insights to.

There are rising levels of security and safety concerns amongst users of sharing services (see Morgan Stanley, 2017; eMarketer, 2018). Hence, the third part of our survey revolved around

---

[9] A cross-sectional survey is a descriptive observational study that analyzes data from a population, or a representative subset, at a specific point in time (Lee, 1994).

[10] The complete survey is found in Appendix 2.

different areas for improvements in sharing services and host attractiveness. This included secure payment systems, review systems, communication and insurance attributes. Here, we aimed to measure what customers value in current offerings, and in which areas the need for improvements is most urgent. To relate our findings to consumer characteristics, the fourth part mapped personal information and personality characteristics. To measure personality traits, we used the Big-Five framework (see Gosling, Rentfrow & Swann Jr, 2003). This is a brief 10-item measure of different personality traits that enjoys considerable support (see John & Srivastava, 1999; McCrae & Costa, 1999). Furthermore, we included three items regarding the respondents' innovation orientation and technology scepticism, adopted form Jahnamir & Lages (2016), in addition to asking our respondents about their attitude and interest in crypto-related attributes (i.e., cryptocurrencies, cryptography, information security).

We designed the survey to induce a feasible representation of Norwegian consumers and non-consumers of home-sharing platforms. In effect, although we acknowledge that additional insights could have been obtained, we excluded questions regarding blockchain technology. This is because we believe blockchain technology, and particularly blockchain-based home-sharing, to be a relatively unfamiliar concept to the general population. Instead, we designed the survey to assess the needs, drivers of use and behaviours amongst current sharing service consumers, with the aim of using these insights to predict future adoption of blockchain-based home-sharing.

The questions in the survey used two different scales to collect data from the respondents; ordinal (i.e., ordered categories where the distance between the categories are not known) and nominal scale (i.e., ordered categories where the distance between the categories are known). Most questions used a 7-point ordinal Likert scale. These scales had slight differences in formulation, but were mostly consistent with a scale where 1 represented "Not important" or "Strongly disagree", and 7 represented "Very important" or "Strongly agree". The nominal scale was primarily used to assess personal information about respondents, such as age, income and personality characteristics. For further details on the survey design we refer to Appendix 2.[11]

Data Collection

Our respondents were collected through *convenience sampling*, meaning that the subjects were selected due to their close proximity to the researchers (Saumure & Given, 2008). In order to investigate different measurements at the same point in time, we deployed a cross-sectional survey, enabling us to reveal interconnection between the variables (Bryman, 2016). The cross-sectional design was also chosen with the purpose of gathering large amounts of data, thus enhancing the generalizability of our findings (Bryman, 2016). Moreover, it limits interviewer biases and variability, which is often associated with qualitative approaches.

[11] The survey was distributed in Norwegian, but is translated to English to enhance the understanding and reproducibility for non-norwegian readers.

The survey was distributed through social media channels (Facebook and LinkedIn) and publicly available Facebook-groups with focus on either the sharing economy, Airbnb, cryptocurrencies or blockchain technology. In addition, we distributed 800 surveys in paper format around several campuses at the Norwegian University of Science and Technology with an attached QR-code linking to the survey. The collection of responses was conducted between March 19th to April 3rd., 2018, and we got 518 unique respondents, where 353 participants completed the entire set of questions. Due to the electronic distribution of our survey through social media, we are unable to assess an accurate response rate. However, as all respondents who received the QR-code answered through a mobile version of the survey, we were able to distinguish responses in relation to distribution channel, showing that 16 percent entered the survey through the QR-code while 84 percent accessed it through social media platforms.

Selection Criteria and Screening of Data

One of the advantages of quantitative methods is their ability to "use smaller groups of people to make inferences about larger groups that would be prohibitively expensive to study (Holton & Burnett, 1997, p. 71)." As a result, a sufficient and unbiased sample size is essential. Hence, in an attempt to reach many potential users of blockchain-based home-sharing platforms as possible, people above 18 years able to understand Norwegian were eligible to participate in the survey.

While Martin, Bateson and Bateson (1993) suggest that larger data samples enhance statistical power, various rules-of-thumb regarding sufficient sample size have been put forward. According to Boomsma (1985), a required minimum sample size is 100 or 200, while Kline (2005) recommends to consider at least 200 respondents to reduce potential biases. When dealing with *Structural Equation Modeling* (SEM) (as used in our analysis), scholars argue that when three or more indicators per factor exist, a sample size of 100 will be satisfactory for convergence, while a sample size of 150 is often sufficient for a convergent and proper solution (Gerbing & Anderson, 1984). Considering that our survey collected 518 unique responses (where 353 were fully completed), our sample size is adequate for statistical analysis and generalizability.

Despite a sufficient sample size, the degree to which our sample is representative of the defined target population depends on how we approach and control the data (Sudman, 1976, cited in Hair et al., 2003). Missing data is a common difficulty within survey-based research, as it can reduce the statistical power of a study and produce biased estimates (e.g., Kang, 2013). Kim & Curry (1977) argue that for any large data set, and especially those relying on how respondents report behavior and attitudes, it is almost certain that some information is either missing or in an unusable form. Consequently, in order to identify missing data or careless responses before conducting statistical analyses, we performed a post hoc data screening.

To eliminate careless responses, two simple tests were performed to uncover respondents who had either (1) finished the survey within an unreasonable short time frame, implying that they only skipped through the question without reading them, or (2) checked the same score on all questions with a Likert scale, implying that they did not care about answering honestly (Meade

& Craig, 2012). The first condition was checked by measuring time elapsed when answering the survey, whereas the second condition was controlled by calculating the variance of the individual responses in MS Excel. A variance close to 0 would then reveal respondents who had given the same answer to nearly all questions. As we believe these responses to be invalid, they were removed from our data set to increase overall quality. Additionally, one case where the respondent was below 18 years of age (i.e., not fulfilling the requirements for participation) was excluded, leading to the removal of 62 respondents, reducing the sample size to 454.

Another issue with survey analysis is missing data, which could bias estimation (Kang, 2013). There exist contradictory opinions regarding treatment of missing values, whereas the most commonly used are the methods of listwise deletion (i.e., not include cases that have missing values in any of the variables under analysis) or pairwise deletion (i.e., include all cases with valid data points, only exclude the missing value in relevant analysis) (Kim & Curry, 1977; Peugh & Enders, 2004). Hair et al. (2014) argue that when missing data in an observation exceeds 15 percent, the observation should be removed from the data set. Considering the missing data in our data set, we have chosen to deploy the method of listwise deletion for all inferential statistics (Pearson correlation and Structural Equation Modeling) to improve the rigor of our analysis. Additionally, listwise deletion provided the best approximation of normal distribution to our variables, and we believe our sample size to be large enough to not significantly weaken statistical power. Moreover, several researchers have found pairwise deletion to be unsuitable for multivariate and contemporary statistical analyses like SEM (Little, 1992; Marsh, 1998; Wothke, 1993). Nevertheless, for the descriptive statistics (i.e., respondent characteristics, means, SD etc.), we used pairwise deletion to give a broader overview.

Limitation in the Data Material

A limitation in our data material relates to the respondent's similarity in age, as 56.1 percent are between 18 and 25 years. Consequently, it is reasonable to assume that the data does not represent an accurate overview of the older age groups, which present a limitation for age-related analyses. However, as the millennial generation is driving the growth of the sharing economy (Ranzini et al., 2017), we consider it as more important to accurately map attitudes and experiences of younger generations.

An overview of characteristics of the respondents is given in Table 3.

Table 3 Overview of respondents

	Percentage	N
Age		362
18 - 25 years	56.1%	
25 - 35 years	14.6 %	
36 - 45 years	13.5 %	
46 - 60 years	11.9 %	
> 60 years	3,9 %	
Gender		361
Male	45.7 %	
Female	53.7 %	
Other	0.6 %	
Income (1,000 NOK)		353
0 - 50	19.0 %	
50 - 200	26.3 %	
200 - 350	7.1 %	
350 - 600	26.6 %	
600 - 800	11.3 %	
800 - 1,000	5.1 %	
> 1,000	4.5 %	
Education		354
High School	17.2 %	
Bachelor's degree	29.7 %	
Masters degree	50.8 %	
Ph.D.	2.3 %	
Hometown		354
Big city	80 %	
Smaller city	16 %	
Rural area	6 %	

4.4 Methods of Analyses

The quantitative data was analyzed through descriptive and inferential statistics. The Airbnb data was analyzed using Microsoft Excel v15.25.1, and the survey data was analyzed using IBM SPSS Statistics version 25 and Stata/MP version 15.1. In this section, we present our analysis of the publicly available Airbnb data (Section 4.4.1), and describe the statistical modeling deployed on our survey responses (Section 4.4.2).

4.4.1 Airbnb Market Analysis

To analyze the market potential of home-sharing platforms, we extracted data from two distinct points in time, with measures made approximately one year apart. We then calculated the following measures for each of the seven cities: Total number of listings, average price per night and average availability (in days/year).

4.4.2 Exploratory SEM Analysis on Survey Data

According to Sarstedt et al. (2014) and Kothari (2004), *exploratory modeling* presents a fruitful path in situations where the empirical or theoretical basis is weak (see 4.2). Exploratory studies are "[…] used in a more free-form fashion, supporting the purpose of capturing relationships that are perhaps unknown or at least less formally formulated (Shmueli, 2010, p. 297)." According to Reinartz (2009), SEM is a modeling approach superior in terms of exploratory research (Reinartz, 2009). It is also widely used in social sciences (Cheung & Rensvold, 2002). Hence, we perceive SEM to represent the best suitable technique for presenting our data.

As shown in Figure 9, SEM analysis combines exploratory factor analysis and multiple regression to best describe a set of interdependent relationships (Ullman & Bentler, 2012; Hair et al., 2012). This allows a dependent variable to become an independent one in a subsequent dependence relationship (Hair et al., 1998). Consequently, we are able to assess the significance and strength of a particular relationship in the context of the entire model. Compared with multiple regression procedures, SEM is a more powerful multivariate technique, as it accounts for the correlated independencies, measurement errors and multiple latent independencies (Byrne, 2001). Thus, it enables us to measure both direct and indirect influences, in addition to carry out test models with multiple dependent variables using several regression equations concurrently (Alavifar, Karimimalayer & Anuar 2012). Moreover, SEM is argued to be a suitable method for sample data exceeding 200 respondents (Snoj et al., 2004).

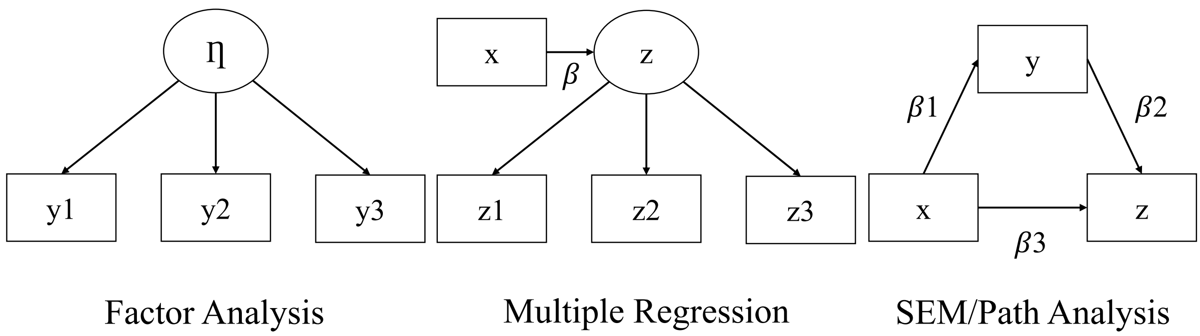

Figure 9: Overview of statistical methods (Adapted from Edelsbrunner & Thurn, n.d.)

Statistical Modeling

Inspired by Kline (2011), our statistical modeling using SEM consists of six distinct parts. The five first steps will be described in more detail in the following sections, whereas the sixth step (i.e., presenting the results) is presented in Chapter 5.

Step 1: Exploratory Factor Analysis and Variable Constructs

The initial process of establishing variables for the SEM analysis is driven by findings from literature and educated guesses (Lei and Wu, 2007). Hence, one of the challenges in these early specifications is to identify and produce a unique set of variables (Kline, 2011). Confirmatory Factor Analysis (CFA) in SEM is the usual approach for establishing these variables (Jöreskog, 1969; Schreiber et al., 2006). However, such analyses require that the researcher has specific expectations regarding the number of factors, which variables reflect given factors, and whether the factors are correlated (Thompson, 2004). Hence, considering our exploratory study, an *exploratory multiple factor analysis* (EFA) with Cronbach's alpha reliability tests analysis was performed (Asparouhov & Muthén; 2009; Marsh, Morin, Parker & Kaur, 2014). The purpose with the EFA was to gain a preliminary understanding of the nature of constructs existing in our data set. In addition, it enables the researcher to simplify interferential statistics, and assess the reliability and validity of the latent constructs (Brown, 2014; Field, 2009).

Constructed Factors and Single Items

Factor analysis involves grouping similar questions or items from the questionnaire into a common dimension (Kinnear & Gray, 2009). This activity is performed when the same dimension is described by several variables in the data set. Hence, factor analysis is used to ensure that the intended constructs can be justified, meaning that variables measure what they were intended to measure, and are not highly correlated with each other (Field, 2009).

In the EFA, we applied the Maximum Likelihood estimation based on the eigenvalues-greater-than-one rule, and the Varimax rotation method in IBM SPSS Statistics, suppressing all coefficients less than 0.5 (Field, 2005). Moreover, to ensure reliability in the constructs, the Cronbach's alpha test was performed on all factor variables. The Cronbach's alpha measures the internal consistency between the questions, and thus tells the researcher how closely related the set of questions in a constructed variable are. In accordance with recommendations from numerous scholars (e.g., Nunnally, 1978; Hair et al., 1998), a Cronbach's alpha value greater than 0.7 was preferred in our study. However, due to the exploratory nature of our research, we also accepted values above 0.6, as proposed by e.g., Nunnally and Bernstein (1994) and Moss, Prosser and Costello (1998).

We initially performed the three distinct factor analysis on Likert scale survey items. We considered 13 statements regarding the respondent's orientation and interests (see Item 10, 11, 21, 22 and 23, Appendix 2), which led to the extraction of the three-indicator Innovation Orientation, two-indicator Technology Scepticism and three-indicator Trust Orientation. These factors serve to characterize how different personal attitudes could influence adoption of home-sharing.

Secondly, we included all seven statements assessing host attractiveness (Item 9, Appendix 2), which led to extraction of the four-indicator Host Service construct. The construct is intended to measure how consumers value host performance, and includes indicators of good reputation, effortless communication and simple payment procedures. Finally, the analysis was run on five questions concerning platform improvements (Item 12, Appendix 2), ending in the extraction of the three-indicator Platform Service construct. This construct is intended to measure how consumers value improvements in the underlying platform infrastructure, and includes indicators regarding enhanced safety in payment systems, more insurance for shared assets and increased privacy protection.

Considering the importance of blockchain technology in our study, we aimed to assess how interest in cryptocurrencies, cryptography and information security would relate to other variables. Hence, we extracted three questions (Item 23a, 23b and 12d) to form a variable for cryptocurrency interest. This construct performed satisfactory with regards to reliability, and led to the formation of Crypto Adptopion. The final constructs and their related Cronbach's alpha are listed in Table 4.

Table 4 Overview of Variables

Constructed Multiple Variables	Name	Mean	St.dev	N
Innovation Orientation (Cronbach's Alpha = 0.78)		5.15	1.05	345
I am...				
21a: Open to trying new products/services	Innovation1	5.42	1.35	323
21b: Quick to adopting new technological innovations	Innovation2	4.95	1.51	322
21c: Supportive of entrepreneurial companies	Innovation3	5.01	1.56	322
Trust Orientation (Cronbach's Alpha = 0.79)		5.06	1.17	322
10a: I feel equally safe when I use sharing services as traditional actors	Trust1	4.85	1.58	323
10b: I trust people I transact with in sharing services	Trust2	4.85	1.32	322
10c: I trust the institution (e.g. Airbnb) behind the sharing platform	Trust3	5.50	1.34	322
Technology Scepticism (Cronbach's Alpha = 0.75)		2.80	1.37	352
I consider myself as...				
22a: Slightly afraid of high-technological solutions	Scepticism1	2.45	1.51	352
22b: Skeptical towards ideas I don't immediately understand	Scepticism2	3.14	1.56	352
Crypto Adoption (Cronbach's Alpha = 0.658)		3.17	1.29	308
23a: I am interested in cryptocurrencies	Crypto1	3.09	1.90	308
12d: I would like to be able to pay with cryptocurrencies on Airbnb	Crypto2	1.98	1.50	308
23b: I am interested in information security and cryptography	Crypto3	4.44	1.63	308
Host Service (Cronbach's Alpha = 0.645)		6.71	0.75	373
9c: I value the reputation of the host	HostS1	6.55	0.90	379
9d: I value easy communication with the host	HostS2	6.21	0.96	377
9f: I value simple and secure payment solution	HostS3	6.54	0.84	379
9g: I value solid insurance schemes	HostS4	5.51	1.49	377
Platform Service (Cronbach's Alpha = 0.695)		5.24	1.25	317
12b: I want more safety around payment systems in home-sharing	PlatS1	5.35	1.64	320
12c: I want better insurance for shared assets	PlatS2	5.12	1.52	319
12e: I want better privacy protection	PlatS3	5.23	1.61	322

Variables can consist of two indicators (as with Technology Scepticism), or even single indicators, when more indicators per factor is unfeasible (Anderson & Gerbing, 1988; Bagozzi and Yi, 2012). However, their psychometric characteristics (i.e., validity and reliability) need to be sufficient to not weaken the results (Kline, 2011). In our analysis, some single item variables are considered important indicators in our statistical modeling. These single-indicator variables are presented in Table 5. Moreover, to better understand how personal characteristics affect the attitude and behaviour of consumers, a set of questions regarding personal information serve as control variables for assessing differences in consumer behaviour and needs, including Age, Gender, Income and Educational Level as displayed in Table 5.

Table 5 Overview of single-indicator and control variables

Single-item Construct	Mean	Std. Deviation	N
3a: HomeSharing	1.73	0.85	388
I have used Airbnb as a guest (from never to > 10 times. 5 pt Likert scale)			
4a: Uber	2.14	1.45	344
I have used Uber (5 pt Likert scale)			
5: Sharing Experience	5.06	1.57	403
I have good experieces with sharing services			
11b: Data sceptisim	5.03	1.81	319
I do not like that sharing platforms utilize my data history			
9b: Price Service	5.32	1.36	378
I value low prices when I seek accommodation			
13: Age	2.93	1.23	362
14: Gender	1.55	0.51	361
19: Income	3.18	1.70	353
20: Education	3.38	0.79	354

Step 2: Testing Assumptions

To proceed with statistical modeling and assure the validity of the output from Pearson correlation and SEM analyses, our variables were tested against the assumption of *Linearity, Normality*, *Outliers*, *Multicollinearity* and *Homoscedasticity* (Schreiber, Nora, Stage, Barlow & King; 2006; Bryman & Cramer, 2005). However, while traditional regression variables usually serve as either independent or dependent, the equivalent variables within SEM analysis are labelled *exogenous* and *endogenous*, respectively[12]. Due to the exploratory nature of our statistical modeling, it was difficult to coherently distinguish dependent and independent variables at the preliminary stage. Consequently, the assumption analyses are performed on all variables included in subsequent analyses.

Linearity

Linearity implies that for a dependent variable, Y, all predictor variables, (X_i), are linearly related to the dependent variable (Harrell, Lee & Mark, 1996). Linear relationships are checked by inspecting the scatterplots for all related variables in an iterative process. Most of the scatterplots indicated linear relationships, but some cases of non-linearity were found in relation to Gender, Age, HomeSharing and Service Orientation. The linearity of these variables was therefore assessed by examining the residual plots from a regression analysis (Larsen & McCleary, 1972). By inspecting the residual plots (i.e., ensuring that the error terms are evenly distributed), the majority of variables show no severe deviations from linearity. However, the tests revealed that non-linearity issues can exist between HomeSharing or Service Orientation and other constructs and items in subsequent interdependent analysis. Nevertheless, according to Hair Jr, Anderson, Tatham and William (1995), if these violations are not extreme cases,

[12] Both exogenous and endogenous variables can be observed or latent variables (i.e., constructed variables/factors), but exogenous variables can *only* influence other constructs, while endogenous could be affected by both exogenous and other endogenous variables in the model (Hair, Ringle & Sarstedt, 2011).

they are not clear indicators of non-linearity. Hence, we acknowledge the limiting factor of insufficient linearity concerning the Home-Sharing or Service Orientation variable, but still assume there exist sufficient linear relationships amongst our variables to perform further analysis.

Univariate Normality

In order to assess the univariate normality (i.e., assumption of normality for each of the variables in this research independently) in our variables, we used the skewness and kurtosis of the distributions (see Table 6). Skewness is a measure of the symmetry of a variable's probability distribution, whereas kurtosis assess the "tailedness" of the probability distribution of the variables[13] (Hair et al., 2014).

In order to simulate a univariate normal distribution, skewness and kurtosis values should be centered as close to zero as possible[14], indicating symmetrical normal distribution. However, conflicting opinions exist regarding absolute values of skewness and kurtosis that are acceptable to verify the assumption of a univariate normal distribution. Here, we choose to follow the recommendation for sample sizes greater than 300 put forth by West, Finch and Curran (1995), who found that when the absolute skewness value is less than two, and absolute kurtosis (excess) is less than seven (i.e., excess value of four in SPSS), the assumption of normality can be supported. The normality of our variables were also assessed by comparing the means and medians. If the values are approximately the same, it further strengthens the assumption of normality.

As shown in Table 6, all variables utilized in the statistical analysis fulfill the requirements for normality put forward by West et al. (1995). However, we could observe that HostService has a negative skewness of -1.69 and a positive kurtosis of 6.66. This indicate that the majority of respondents have answered at the high-end or right-side of the Likert scale, and that the distribution is heavily peaked. This is an expected deviation, as high Service Orientation (i.e., high reputation, simple and sage payment systems, easy communication and insurance) is considered critical for host attractiveness within home-sharing. Moreover, it should be noted that the HomeSharing variable is positively skewed, indicating a clustering of scores at the low-end or left-side of the graph, which seems reasonable as this variable measures the number of times the respondents have used Airbnb, often not exceeding three times per year (i.e., low-end response).

---

[13] Skewness values > 0 indicate cores clustered to the left (low-end), while values < 0 indicate a clustering of scores at the right (high-end). Kurtosis values > 0 indicate that the distribution is rather peaked (clustered in the centre), with long thin tails, while values < 0 indicate a distribution that is relatively flat (too many cases in the extremes).

[14] For practical reasons, SPSS provide 'excess' kurtosis obtained by subtracting 3 from the kurtosis (proper). Hence, while the empirical kurtosis essentially is 3 for the normal distribution, the excess kurtosis is zero (West et al., 1995).

Table 6 Normality and outlier tests

	Mean	Median	Skewness	Kurtosis	5% Trimmed Mean
Constructed Multiple Variable					
Innovation Orientation	5.15	5.25	-0.53	0.40	5.18
Technology Scepticism	2.80	2.50	0.60	-0.38	2.72
Trust Orientation	5.06	5.00	-0.38	-0.16	5.11
Crypto Adoption	3.17	3.00	0.67	0.30	3.11
Host Service	6.21	6.25	-1.69	6.66	6.28
Platform Service	5.23	5.33	-0.56	-0.11	5.30
Single Item Construct					
Homesharing	1.73	2.00	1.44	2.69	1.64
Uber	2.14	1.00	1.00	-0.48	2.04
Experience	5.06	5.00	-0.47	-0.62	5.13
Data Scepticism	5.03	5.00	-0.57	-0.76	5.14
Price Service	5.32	5.00	-0.46	-0.41	5.39
Age	2.93	2.00	1.02	-0.27	2.82
Gender	1.55	2.00	-0.07	-1.69	1.55
Income	3.18	3.00	0.42	-0.72	3.10
Education	3.38	4.00	-0.52	-0.79	3.40

Multivariate Normality

In order to also assess multivariate normality, the variable's *Quantile-Quantile* (Q-Q) Plot was examined. The reference line of a Q-Q represents a particular distribution (Chambers, 2017), in this case the normal distribution. The majority of the variables show sufficient multivariate normality according to the Q-Q Plots, which strengthens our assumption of approximately normality distribution. However, we could observe a significant deviation in the distribution of the Host Service construct, and the HomeSharing variables, as shown in Appendix 3. According to Kline (2011), many instances of multivariate non-normality can be detected by screening for univariate normality. This also holds for our data set, as our findings from the multivariate approach are all in line with the Univariate analysis. Moreover, the same variables having non-linearity issues seems to also be the ones suffering from non-normality.

West et al. (1995) argue that the effect of non-normality in SEM analysis depends on the extent and source; the greater the extent of non-normality, the greater the magnitude of the problem. However, the majority of raw empirical data in behavioural research will not follow a univariate normal distribution, let alone a multivariate distribution (Micceri, 1989; Gao et al., 2008). Still, lack of normality does present a limitation in the results. Non-linear transformations can be performed in the case of severe non-normality (Kline, 2011; West et al. 1995). However, such a transformation complicates the interpretation of the variables, and there is no guarantee it will result in normality (Gao et al., 2008). Moreover, scholars argue that SEM estimations using the method of Maximum Likelihood is robust against the violation of normality (Chou et al., 1991; Fan and Wang, 1998; Hu et al., 1992), and that moderate non-normality issues have quite negligible effects on such parameter estimation (e.g., Finch et al., 1997). Consequently, as severe non-normality is only present for two variables, we acknowledge that the limitation could affect the statistical analysis (e.g., also chi-square tests assume normality), but made the decision to neither transform nor exclude HomeSharing and Service Orientation.

Outliers

Outliers (i.e., observations that deviates greatly from other observations) may distort parameter estimations, and bias the descriptive and inferential statistics (e.g., Zimmerman, 1994; Blair & Higgins, 1980; Cook & Weisberg, 1980). Considering the Likert scale used in our surveys, the existence of extreme observations is limited. Nevertheless, according to Leys, Ley, Klein, Bernard and Licata (2013), outliers can still occur if a response deviates more than three times the standard deviation from the mean. Consequently, we have investigated outliers through a visual inspection of the variables' boxplot. As we did observe potential outliers for the Innovation Orientation, Crypto Adoption, Host Service and HomeSharing variables, the extreme values was further investigated. We inspected the 5 percent trimmed mean for each variable, showing the mean when 5 percent of the outlier values are extracted from each end (Anscombe, 1960). If there are large differences between the 5 percent trimmed mean and the mean, the chances of outliers affecting further analysis is significant. However, as shown in Table 6, none of the variables show any substantial disparity between the mean and the 5 percent trimmed mean.

Multicollinearity

Multicollinearity refers to the situation where prediction variables are highly correlated with each other. This is an issue in multivariable analysis, as regression modelling is not able to accurately associate variance in outcome variables with the correct predictors, leading to inaccurate results and incorrect inferences (Eikemo & Clausen, 2012). To avoid issues of multicollinearity, substantial correlations ($r < 0.8$) between the predictors should not exist (Bryman & Cramer, 2011; Field, 2009; Eikemo & Clausen, 2012). As further described in Step 4, we performed preliminary bivariate correlation analyses on the constructed factors, single-indicator measurements and control variables. The results of this analysis is presented in Chapter 5, Table 14, and imply no multicollinearity issues in the sample, with the highest reported coefficients existing between Income and Age ($r = .64$, $p < .05$).

The *Variance Inflation Factor* (VIF) indicates whether a predictor has a strong linear relationship with other predictors in the model (Field, 2009), and should be below 10 to ensure that your variables show no excessive signs of multicollinearity (Cohen, Cohen, West & Aiken, 2003; Field, 2005). The VIF was calculated in an iterative process using SPSS, and all values were reported within the interval 1.070 - 2.101, with the majority below 1.5. Hence, we observed no signs of excessive multicollinearity that could affect our results.

Homoscedasticity

Heteroscedasticity occurs when residuals at each level of the predictor variables have unequal variances (Field, 2009). To ensure absence of heteroscedasticity (i.e., homoscedasticity) we inspected the residual plots of the standardized versus unstandardized residuals (Hair et al., 1995). As concluded in the section on linearity, the residual plots do not show many substantial deviations (some regarding HomeSharing and Host Service), which implies no severe violations of nonlinearity and heteroscedasticity.

Step 3: Descriptive Statistics and Pearson Correlation Analysis

We performed descriptive analyses on all relevant variables in order to get an overview of the frequencies of different responses, respondent characteristics, central tendencies of variables, and their dispersion and variability (Mazzocchi, 2008). To further explore our data material and observe underlying relations amongst variables, we performed a preliminary bivariate Pearson correlation analysis. The Pearson's correlation coefficients enable us to accurately measure the linear associations between our variables (Field, 2009), indicating if one increases while the other decreases (negative correlation), or if both increase simultaneously (positive correlation). These analyses also serve to reveal the "relationships between interval/ratio variables and/or ordinal variables that seeks to assess the strength and direction of the relationship between the variables concerned (Bryman, 2016, p. 690)".

In order to perform a reliable Pearson correlation analysis, the variables under investigation must be continuous, and the sampling distribution should ideally be normally distributed and include no severe cases of heteroscedasticity (Field, 2009). As shown in Step 2, the assumption of normality and homoscedasticity holds. However, there are conflicting views as to whether Likert scales can be interpreted as continuous variables for analytical purposes, as they only allow for a a select set of discrete values to be defined within the interval. However, we follow Johnson and Creech (1983), and Sullivan and Artino (2013), who found that ordinal variables with more than five categories can be used as continuous variables without harming the analysis. Consequently, all our 7-point Likert scale items pass the requirement of continuous variables. Still, for some of our categorical control variables, such as Age and Gender, and the HomeSharing and Uber variable (5-point Interval scale), the assumption of continuous variables does not hold. In these cases, for preliminary correlation analyses, we instead performed a Point-biserial correlation, which is a special case of the Pearson correlation that allows you to correlate discrete and continuous variables (Nunnally & Bernstein, 1994).

Step 4 and Step 5: Developing our Measurement and Structural Equation Model

To enhance the understanding of our data set, a SEM was developed. A structural equation according to Bryman and Cramer (2011, p. 361) is "an equation representing the size and direction of the relationship between two or more variables". As an extension of multiple linear regression, a SEM analysis facilitate simultaneously investigation of relationships between several independent and dependent variables. However, as previously introduced, our study employs an exploratory approach. Although the focus of SEM often is on estimating relationships amongst hypothesized latent constructs, the method is also suited to test experimental data, as it allows the researchers to test how constructs are theoretically linked and the directionality of significant relationships (Schreiber et al., 2006). Hence, aiming to provide insights to our third and fourth research questions, and using our theoretical insights from the literature review in Chapter 2 and 3, we aimed to build two distinct structural models to explain the interrelationships between different constructs and independent variables; Model-

1 emphasizing on drivers of home-sharing usage; Model-2 exploring the customer needs for improvements within the same segment.

Following Anderson and Gerbing's (1988) proposal, our SEM analysis follows a two-stage approach: (1) a measurement model referring to the relationships between the research constructs (latent variables) and their indicators, and (2) a structural model, exploring the causal relationships amongst the included constructs. In each analysis, we use the *Maximum Likelihood Estimation* (MLE), which under the assumptions of multivariate normality, and with large sample size (N), arguably gives unbiased, consistent, and efficient parameter estimates and standard errors (Bollen, 1989). The MLE attempts to find the parameter values that maximize the likelihood function, given the observations, and is the most commonly used statistical method within SEM (Anderson & Gerbing, 1988; Kline, 2011).

Measurement Models

The measurement model (also referred to as a CFA) in a SEM analysis intends to interpret the relations between latent variables and their observed indicator variables. Consequently, the primary component of the measurement model consists of testing the reliability of each construct (Cheung & Rensvold, 2002). Furthermore, the measurement model is often used to examine the existence of interrelationships and covariation/correlations amongst the latent constructs. This includes observing factor loadings and unique variances, in addition to inspect the modification indexes, which implies if any variable should be excluded, or if a new path should be added to the model. Moreover, a valid measurement model is a prerequisite to evaluate the structural part of the model (Kline, 2011). Using the EFA and reliability analysis from SPSS as a basis (see Table 4), two separate CFA analyses are performed on Model-1 and Model-2.

Following the recommendation of Holmes-Smith, Coote & Cunningham (2006) for measuring model fit and statistical significance, we have investigated at least one fitness index from each category of *Absolute Fit*, *Incremental Fit*, and *Parsimonious Fit*. Consequently, both measurement and structural models are evaluated in terms of the *root mean square error of approximation* (RMSEA; Absolute Fit test) *Comparative Fit Index* (CFI) and *Tucker-Lewis Index* (TLI)[15] (Incremental Fit tests), the *Chi-square* ($\chi 2$; Parsimonious Fit test) in addition to inspecting the factor loadings.

The CFI is the most reported of the model fit indices, especially due to being one of the measures least affected by sample size (Fan, Thompson & Wang, 1999). A CFI value above 0.95 indicate a relatively good fit between the hypothesized model and the observed data (Hu & Bentler, 1999; Schreiber et al., 2006). Some scholars argue that 0.95 is a conservative limit, thus proposing that CFI > 0.92 (Hair et al., 2011) or CFI > 0.90 (Kline, 2005) is sufficient to indicate good fit of the model.

[15] The CFI and the TFI test compares the hypothesized model against the baseline model, which assumes that no variables are correlated, except for observed exogenous variables when endogenous variables are present.The values range from 0 to 1 (Cheung & Rensvold, 2002).

The RMSEA measures the lack of fit due to misspecification of the model, and is thus sensitive to model misspecification (Hu & Bentler, 1998). A cut-off value of RMSEA below 0.06 is often interpreted as goodness of fit (e.g., Hu & Bentler, 1999; Hooper, Coughlan & Mullen, 2008), but values lower than 0.07 (Steiger, 2007) or 0.08 (Browne & Cudeck, 1993) are also generally accepted. Moreover, it is often recommended to inspect the 90 percent confidence interval for the RMSEA value, where the lower value ideally should be close to zero, and the upper value less than 0.8 (Byrne, 2010).

The Chi-square ($\chi 2$) value is essentially a measure to evaluate overall model fit and is used to assess the amount of discrepancy between the sample and fitted covariance matrices (Hu & Bentler, 1999). According to Sawyer and Page (1984), the smaller the $\chi 2$-value (with a non-significance p-value > 0.05) is compared to the *degrees of freedom* (df), the more confidence can be out into the model describing a sensible relationship between the measured variables. However, while an insignificant $\chi 2$-value suggests goodness of fit, the measure is argued to not present an adequate and reliable guide to model adequacy for large sample sizes (Cheung & Rensvold, 2002). While the $\chi 2$ is a highly sensitive test, it is almost always significant (< 0.05) for large sample sizes (N > 400) (Kenny, 2015), indicating a poor fit (Hu & Bentler, 1998; Cheung & Rensvold, 2002). However, scholars still view the value of $\chi 2$ as fundamental, but alternative fit indexes, such as CFI and TLI, should be reported for all models (Kline, 2011; Bagozzi & Yi, 2012).

Factor loadings represent the regression slopes for predicting indicators for each construct (Brown & Moore, 2012) and should be examined for all measurement models (e.g., Bagozzi & Yi, 1988; Hair et al., 2011). High factor loadings confirm that the indicators are strongly related to their associated latent variable, and should be at least 0.5 (ideally 0.7) and statistically significant (Hair et al., 2011).

There are two methods of running the CFA; CFA for individual models and the CFA for pooled measurement models (Zainudin, 2012). Individual CFA runs every latent variable in the research separately, whereas pooled CFA runs all latent variables simultaneously (Zainudin, 2012). However, individual measurement models are inconvenient when the latent measurement model has less than four indicators. In such cases, Pooled Confirmatory Factor Analysis (PCFA) is suggested (Zainudin, 2012) and proven to provide sufficient results (Chong, Nazim & Ahmad, 2014). While the PCFA runs all the latent variables at the same time in order to achieve the required model fitness, the item deletion process and model re-specification is similar to traditional CFA (Afthanorhan, Ahmad, & Mamat, 2014; Chong, Nazim & Ahmad, 2014).

PCFA on Model-1 - Usage

Starting with the four constructed factors (Innovation Orientation, Technology Skepticism, Trust Orientation and Crypto Adoption) from the preliminary EFA (see Table 4), a PCFA was performed (applying the method of MLE) in Stata. When inspecting the factor loadings, significance level of the initial relations and the fit indexes, the model showed insufficient fit. Consequently, to detect model misspecification, we looked at the Modification Indices (MI). The MIs offer suggested remedies to discrepancies between the proposed and estimated model, giving insights to how the model's chi-square statistic would decrease if a fixed parameter were added to the model and freely estimated (Whittaker, 2012). A high value of MI (> 10) indicates redundancies between that two items (Bryne, 2010). In such events, the researcher should modify the model either by adding statistically significant paths if they make theoretical sense (starting with the largest sensible modification, i.e., the relationship with the highest MI value), or try removing one of the two redundant items, examining how the incremental changes affect model fit for each modification (Whittaker, 2012; O'Rourke, Psych, & Hatcher, 2013).

Employing this strategy led to the removal of the Technology Skepticism latent construct, and resulted in the final Measurement Model-1 as shown in Figure 10, with satisfactory factor loadings for all relations (all above 0.5 with the exception of InfoSec with 0.49), CFI = 0.946, TLI = 0.919, RMSEA = 0.077 (90 percent Confidence Interval (CI): 0.056-0.100), $\chi 2 = 67.466$ with df = 24 (p = 0.000). Consequently, as the $\chi 2$ was expected to be significant ($p < 0.05$) due to the large sample size in our data material, all the results indicate satisfactory good fit, and thus we conclude that Measurement Model-1 gives a reasonable representation of the data.

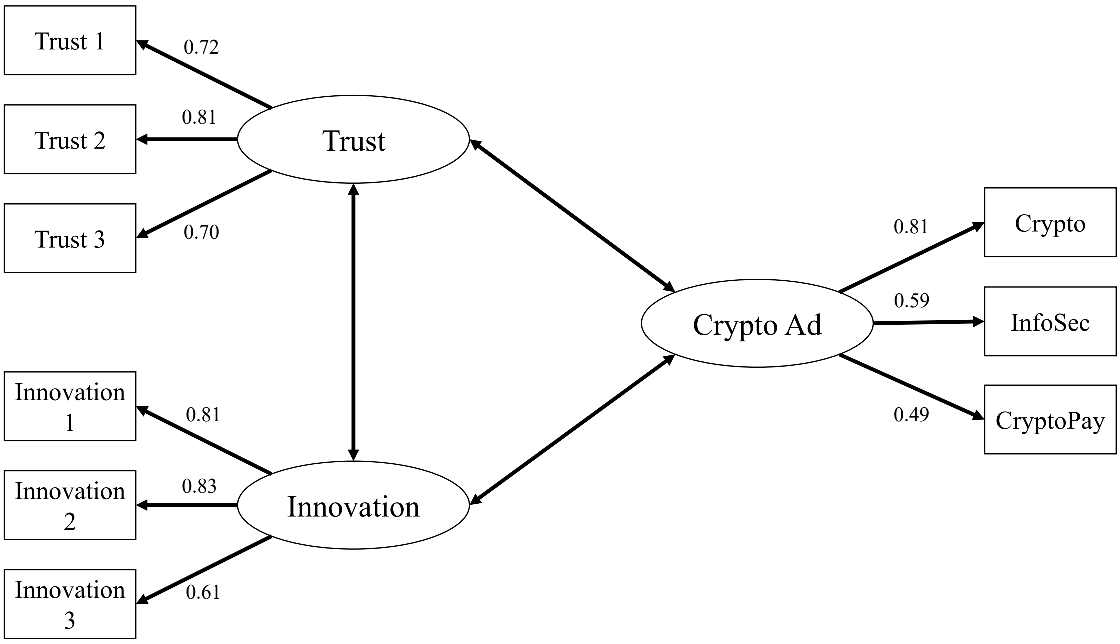

Figure 10: Measurement Model-1

PCFA on Model-2 - Improvements

Using a similar PCFA approach as for Model-1, we used the Host Service and Platform Service from the preliminary EFA (see Table 4) as latent constructs. Inspection of factor loadings, significance level, fit indexes and MI, led to the deletion of the the HostS4 item of the four-indicator construct Crypto Adoption. This resulted in the final Measurement Model-2 as shown in Figure 11, having CFI = 0.984, TLI = 0.970, RMSEA = 0.048 (90 percent CI: 0.000-0.090),

$\chi2$ = 13.789 with df = 8 (p = 0.087). Still, the factor loading of the HostS1 item (= 0.42) is below the general acceptance of a 0.5 limit. Nevertheless, Host Service is conceptually not a tightly linked construct, as the purpose of the variable is to measure how much consumers value the set of different host-related offerings (reputation, communication, payment systems). Thereby, as the overall fit of the model is good, we choose to proceed with HostS1 item in the constructs, and we perceive Measurement Model-2 to be a satisfactorily representation of our data.

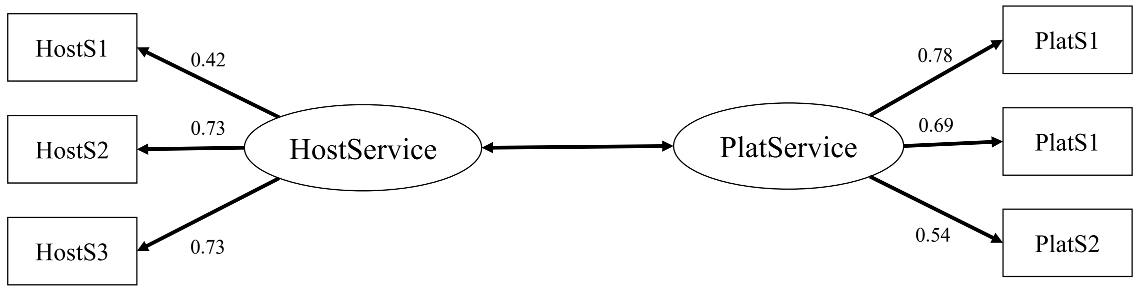

Figure 11: Measurement Model-2

Structural Models

Following the satisfactory results of the two measurement models, we set out to develop Structural Model-1 and Structural Model-2, aiming to assess the relationship between the constructed latent variables and single-indicator measurements.

In SEM, two types of relationships are feasible amongst the constructed and single-indicator measurements: (1) *dependence relationship*, which is depicted by a straight arrow and used between an exogenous construct and an endogenous construct, and (2) *correlation relationship*, which is depicted by a two-headed arrow, and used only between exogenous constructs (as used in the pooled CFA). Hence, when running the SEM analysis, applying standardized values and the method of MLE, it provides three distinct estimates: (1) the path coefficient or standardized regression coefficient (β) for the dependence relationship, which indicate the regression slopes for predicting indicators from the latent factors (i.e., average increase/decrease in Y for each unit change in X, adjusted for all other variables in the model which are held constant), (2) the correlation coefficients (for any correlated and linked items in the model), and (3) the variance in each indicator that is not accounted for the latent factor, representing the measurement error (Hair et al., 2011). The latter can also be utilized to compute the standardized R-squared value for each variable[16], representing the amount of explained variance in the endogenous variable from its associated indicators (Hair et al., 2014).

As for the measurement models, we examined the goodness of fit indexes and MI for model re-specification or modification. Baron and Kenny (1986) recommend that all possible

[16] R-squared can either be computed by the formula (R-squared = 1 - the unexplained variance squared), or by running an equation-level goodness of fit analysis in Stata, both providing the same results.

relationships between the variables in the SEM model should be tested. Hence, using our measurement models as basis, the process of establishing our final structural models was recursive. We adjusted the models by including or excluding different variables, and explored different significant path dependencies. We also checked the p-values and 95 percent CI to assess the significance of each relationship, as a p-value < 0.05 and a small confidence interval imply significance.

The theoretical reasoning and modification decisions behind our two final structural models are described in more detail in Section 5.4, including visual representations (see Figure 12 and 13) and model-fit test results. Furthermore, SEM analyses using MLE estimation were performed on each structural model, assessing the direct effects in our model. However, one of the advantages of SEM is that it also could assess indirect effects (Baron & Kenny, 1986), which allows us to examine the effect of a variable (often exogenous) on an endogenous variable through a mediating variable. Hence, a supplementary analysis was performed to examine if there existed any significant indirect relationships towards the variables of highest interest in our structural models.

4.5 Quality of Research

A critical aspect of research is to establish a set of criteria to evaluate what good research actually is. Here, researchers argue that one needs to assess the validity and reliability of findings to sufficiently evaluate the quality of research (Lincoln & Guba, 1985; Golafshani, 2003). The findings from both the literature review (Section 4.5.1) and statistical analysis (Section 4.5.2) are assessed in the consideration of reliability and validity.

4.5.1 Validity and Reliability of Findings from Literature Review

With regards to results based on literature reviews, we follow recommendations from Golafshani (2003), and assess validity and reliability by looking at credibility, transferability, dependability and confirmability. As the literature review is an extension to the review in our preceding project thesis, the upcoming assessment is somewhat coinciding with the prior assessment of the quality of research (Boge & Nyrønning, 2017).

Credibility

Credibility involves establishing if the results of the conducted research is believable, and thus reflects the researches confidence in the “truth” of the findings (Gay, Mills & Airasian, 2009). As the retrieved information on blockchain technology in many cases seemed to be colored by either very pessimistic or enthusiastic and overly optimistic views, it could potentially affect the credibility of our representation and conclusions. Hence, in order to enhance the credibility of our literature review we have applied triangulation of sources, as described in Section 4.3.1. By doing so, we sought a convergence amongst the obtained information, and critically examined information that was inconsistent with this convergence.

Dependability

Dependability is defined by Lincoln & Guba (1985, p. 299) as "seeking means for taking into account both factors of instability and factors of phenomenal or design induced changes", and reflects the degree to which data changes over time and alterations made in the researcher's approach during the analysis process. The problem of inconsistency in retrieved data is most critical when the data collection is extensive and extends over a longer period of time. Hence, as our thesis was written within a time frame of only five months, in addition to us actively seeking new publications within our area of research, we consider the dependability of retrieved data and findings to be high.

Transferability

Transferability refers to the extent of which the results can be generalized or transferred to other contexts (Guba, 1981). While our research has been concerned with how blockchain-based home-sharing platforms can succeed in the sharing economy, we argue that the outcome of our analyses can be transferred to other sharing-initiatives (e.g., car-sharing, object-sharing) or digital consumers-related platforms that could benefit from utilizing the same attributes of blockchain technology.

Confirmability

When arguing for confirmability, researchers need to persuade the reader that their research is not overly influenced by personal values or theoretical inclinations (Bryman, 2008). As previously mentioned, our preliminary literature review encompassed a broad selection of sources, ranging from scientific articles to more subjective newspaper articles and posts on technological forums. The fact that we engaged in such a broad search for information provided us with insights in both pessimistic, neutral and overly enthusiastic perspectives. This provided us with an understanding to help pinpoint credible sources, and thus enhance the degree of conformability.

4.5.2 Validity and Reliability of Statistical Findings

To ensure general reliability in our research, we have provided a detailed description of all steps performed throughout our study, thus facilitating its reproducibility (Yin, 2013). Moreover, as described in Sections 4.4.2 and 5.4, we have used goodness of fit indexes to ensure validity and reliability of our models. Additionally, the coefficients of determination for both our final SEM models are substantial (0.97 and 0.65, respectively), thus reinforcing the quality. We also note that the majority of estimated path coefficients have values of considerable size, strengthening our explanative contribution (Ringle & Spreen, 2007)

However, with regards to statistical modelling such as SEM, the quality of the final results are dependent on capturing and establishing the validity and reliability of the underlying constructs. As Schreiber et al. (2006, p. 335) state, "The power of SEM is seen most fully when multiple indicators for each latent variable are first tested through CFA to establish the conceptual soundness of latent variables used in the final structural model. Without empirical evidence that such is the case, the relationships that the authors found significant in the structural model may be misleading." Hence, the following sections will further assess the quality of our research by discussing the construct validity and the reliability of our final SEM models. Additionally, we will assess the external validity of our findings.

Construct Validity

Construct validity is an assessment of the quality of the experimental design, and is concerned with whether the constructs are measuring what they are indented to measure or not (Babbie, 1989). Without construct validity, the researcher is thus more likely do draw incorrect conclusions. By following the two-stage recommendations of Anderson and Gerbing (1988), construct validity for our latent variables are already confirmed based on goodness-fit-indices in the CFA (Hsieh & Hiang, 2004) and factor loadings greater than 0.50 (Holmes-Smith, Coote & Cunningham, 2006) for all latent constructs with the exception of the HostS1 indicator in the Host Service constructs (see Section 4.4.2). However, we aim to provide further support for the construct validity by assessing discriminant and convergent validity (Andrews, 1984; Schumacker, 2004).

Discriminant validity is concerned with whether a latent construct shares more variance with its indicators than it shares with other constructs in the model (Hulland, 1999). The discriminant validity can be assessed with the Fornell-Larcker criterion, which states that the *Average Variance Extracted* (AVE) for each construct must be greater than the variance shared between the construct and other constructs in the model. In other words, AVE of a latent variable should be greater than the squared correlation of the variable with each of the other latent variables in the model (Hair et al., 2011). The Fornell-Larcker test is conducted on both measurement models. By assessing the squared correlation and the AVE (using the factor loadings), we could observe that all our constructs fulfill the Fornell-Larcker criterion (see Table 7 and 8), thus providing evidence for discriminant validity.

Table 7 Assessing discriminant validity for measurement model-l

	1	2	3
1. Innovation Orientation			
2. Trust Orientation	.22*		
3. Crypto Adoption	.20*	.01*	
AVE	**.57**	**.55**	**.42**

Table 8 Assessing discriminant validity for measurement model-2

	1	2
1. Host Service		
2. Platform Service	.18*	
AVE	**.41**	**.46**

Convergent validity relates to the internal consistency of the indicators in each construct, and measures to what extent a latent variable explains the variance of its indicator. To assess the convergent validity, we examined the AVE values for each construct based on our factor loading. The AVE should be greater than 0.5, indicating that the construct on average explains more than one-half of the variance of its indicators (Hair et al., 2011). Innovation Orientation and Trust Orientation exhibit AVE values at the level of ensuring high convergent validity. Platform Service is close to the threshold, while both Crypto Adoption and Platform Service has an AVE just above 0.4. Hence, these insufficient values should be taken into consideration, and presents a limitation to our study.

Reliability

Reliability refers to the "consistency of a measure", and thus assesses whether a measure is able to provide consistent results under constant conditions, and if its indicators function as reasonable proxies for the latent variable (Bollen & Lennox, 1991; Nunnally, 1978). The reliability of our SEM models was first investigated by their internal consistency. Internal consistency reliability concerns whether the items measuring a construct are similar in their scores (Hair et al., 2014), and is usually examined by the factor's Cronbach's alpha. The Cronbach's alphas were calculated for each construct and measured against the same recommendations as described in Section 4.4.2 (ideally > 0.7, but > 0.6 is satisfactory for exploratory studies). Secondly, we looked at the *Composite Reliability* (CR) using our factor loading to measure the ratio of true composite variance (latent variables) to observed composite (items) variance of scores. The CR should be above 0.6 (Bagozzi, 1991), but ideally above 0.7 (Fornell & Larcker, 1981). As shown in Table 9, all the latent constructs have a Cronbach's alpha and CR above 0.6, and most are above or close to 0.7, indicating good reliability (Field, 2009; Hair et al., 2011).

Table 9 Reliability test for latent constructs

Latent Construct (Model)	Cronbach Alpha*	Composite Reliability
Innovation Orientation (M-1)	0.78	0.80
Trust Orientation (M-1)	0.79	0.79
Crypto Adoption (M-1)	0.66	0.67
Host Service (M-2)	0.68	0.67
Platform Service (M-2)	0.70	0.71

*The Cronbach's alphas computed in this section are those for the final constructs in the measurement models. Hence, for Host Service, this will differ from those values shown in Table 4, as the HostS4-indicator was deleted in the CFA.

External Validity

External validity is concerned with generalization, and is related to the extent of which the results is transferable to other contexts or populations (Guba, 1981). In order to assess the external validity, the researcher needs to evaluate whether the findings from the study can be transferred to individuals whose place, time and circumstances differ from the participants in the study (Johnson & Christensen, 2004). As our responses were collected through convenience sampling (i.e., a non-randomized selection), we have no means of knowing whether the larger population is represented by the partly 'self-selected' sample. Inevitably, this could reduce the generalizability of the results. Additionally, our survey was restricted to Norwegian respondents, which might limit transferability to other countries. As most of our respondents were young adults, who often are more adoptive of digital technologies, it might result in a slightly biased representation of the findings.

5 Results

In this chapter we present the results from the Airbnb market analysis, and the correlation and SEM analyses based on our survey. These results, in combination with the reviewed theoretical and empirical literature in Chapter 2 and 3, constitute the basis for discussing our research questions in Chapter 6.

5.1 Airbnb Market Analysis

To develop an understanding of the current home-sharing market, we analyzed data from seven cities in relation to changes in prices, number of listings and availability on Airbnb between 2016 and 2017. The growth within each respective measure is shown in Table 10.

Table 10 Airbnb Overview

Amsterdam	**Price (USD)**	**Listings**	**Availability (days/year)**
2016	151.4	13,269	120.6
2017	163.2	16,102	74.9
Growth	7.75 %	21.35 %	-37.86 %
Barcelona	**Price (USD)**	**Listings**	**Availability (days/year)**
2016	93.4	14,223	233.1
2017	101.2	14,869	203.0
Growth	8.36 %	4.54 %	-12.89 %
Copenhagen	**Price (USD)**	**Listings**	**Availability (days/year)**
2016	112.2	11,705	140.6
2017	117.0	16,416	97.3
Growth	4.32 %	40.25 %	-30.77 %
San Fransisco	**Price (USD)**	**Listings**	**Availability (days/year)**
2016	198.3	6,966	157.8
2017	200.5	6,020	141.5
Growth	1.10 %	-13.58 %	-10.32 %
Toronto	**Price (USD)**	**Listings**	**Availability (days/year)**
2016	89.7	7,243	210.3
2017	91.0	9,871	165.6
Growth	1.38 %	36.28 %	-21.23 %
Sydney	**Price (USD)**	**Listings**	**Availability (days/year)**
2016	132.7	14,630	149.9
2017	137.1	19,778	121.2
Growth	3.30 %	35.19 %	-19.13 %
New York	**Price (USD)**	**Listings**	**Availability (days/year)**
2016	138.6	31,078	170.6
2017	136.7	36,462	139.9
Growth	-1.35 %	17.32 %	-18.01 %
Overall Growth (all cities)	**2.43%**	**20.47%**	**-18.43%**

The average number of listings across all cities show an overall growth of 20.47 percent, witnessing a substantially increase in supply of Airbnb apartments. However, the change in number of listings vary between the different cities, ranging from a 13.58 percent decrease in San Francisco, to a 38.28 percent increase in Toronto.

For the average rental price of listings across all cities, we observe a 2.43 percent increase. Still, we observe significant variations among the different cities, and European cities have in general experienced more rapid growth compared to their counterparts in Australia and North America. For example, prices in Barcelona and Amsterdam, increased by 8.4 percent and 7.8 percent, respectively, while prices in New York decreased by 1.3 percent.

The overall availability of listings decreased by 18.24 percent, meaning that the average occupancy rate increased across all cities. The changes in availability exhibit similar characteristics as the price changes, as European cities experienced a larger decrease in availability compared to cities in North America and Australia. We also observe a deviation for San Francisco and Barcelona, which show an decrease in availability of 10.32 percent and 12.89 percent, respectively, which significantly differ from the highest decease of 37.85 percent in Amsterdam.

5.2 Descriptive Statistics on Survey Data

In the two following subsections, we present general descriptive statistics (i.e., frequencies, means and standard deviations) from our survey regarding consumer behavior and characteristics and need for improvements in the home-sharing market.

5.2.1 Consumer Behavior and Characteristics

Our first survey questions related to previous use of sharing services, in which 91 percent of the respondents reported previous experience, and 54 percent had used Airbnb as a guest during the past two years. Table 11 shows descriptive statistics of the questions where respondents were asked to describe their frequency in sharing service usage on a scale from 1 to 5 (see Item 2-4, Appendix 2). By looking at the use of Airbnb (mean = 1.73, SD = 0.85) and Uber (mean = 2.14, SD = 1.45), most of our respondents have used sharing services between 1-3 times during the past year. Most of the non-consumers of sharing services stated that they had never felt the need to use sharing services, or that they preferred to transact with traditional actors.

The remaining questions used a 7 point Likert scale to identify consumer behavior and characteristics. Our results show that (1) people generally have good experiences with sharing services (mean = 5.06, SD = 1.57), (2) people are somewhat reluctant to share personal information with sharing platforms (mean = 5.03, SD = 1.81), and (3) they position themselves as neutral as to whether online reviews on sharing platform are fake (mean = 3.65, SD = 1.39). However, these measures all have high standard deviations, implying that the opinions are widely dispersed.

Consumers pointed out that they feel moderately safe when using sharing services (mean = 4.85, SD = 1.58) and transacting with strangers (mean = 4.85, SD = 1.32). Still, their trust in institutions (i.e., the sharing platform) is notably higher (mean = 5.50, SD = 1.34). Furthermore, people search for additional information (e.g., through Google) about people they transact with, as they believe sharing platforms provide insufficient amounts of information (mean = 4.73, SD = 1.82).

When measuring the interest in cryptocurrencies and information security, we observed that the general consumer is not interested in cryptocurrencies (mean = 1.98, SD = 1.50), while a substantial amount reported to be interested in information security, including cryptography, privacy protection and data criminality (mean = 4.44, SD = 1.63).

Table 11 Descriptive statistics regarding consumer behaviour and experience

	N	Mean	Std. Deviation
I have used sharing services (1 = yes, 2 = no)	454	1.09	0.29
Usage Measurements in 2017 (5 pt. Interval Scale)			
Yearly Airbnb usage as guest, from never (= 1) to >10 times (= 5)	388	1.73	0.85
Yearly Uber usage from never (= 1) to >10 times (= 5)	344	2.14	1.45
Experience With Sharing Services (7 pt. Likert scale)			
I have good experiences with sharing services	403	5.06	1.57
I do not like that sharing services utilize my data history	319	5.03	1.81
I often think online reviews are fake	319	3.65	1.39
Trust In Sharing Services (7 pt. Likert scale)			
I feel equally safe when I use sharing services as traditional actors	323	4,85	1,58
I trust people I transact with in sharing services	322	4,85	1,32
I trust the institution (e,g, Airbnb) behind the sharing platform	322	5,50	1,34
I search (e.g., through Google) for more information regarding strangers I transact with online	320	4,73	1,82
Cryptocurrency and Information Security Interest (7 pt. Likert scale)			
I am interested in cryptocurrencies	352	1.98	1.50
I am interested in information security and cryptography	352	4.44	1.63

5.2.2 Mapping the Demands for Improvements in Sharing Services

In order to understand how blockchain can be utilized to maximize perceived value amongst potential future consumers, we included a set of question to identify what consumers value when booking accommodation from an independent host (i.e., a host operating outside Airbnb). The result of this analysis is displayed in Table 12, and shows that a good reputation (mean = 6.55), easy and secure payment systems (mean = 6.54), and effortless communication (mean = 6.21) are considered most important. Further, the survey shows that people also value solid insurance schemes (mean = 5.51), low prices (mean = 5.32) and available information on the host (mean = 5.02). The personality of the host is not considered important (mean = 2.92).

By looking at the consumers' evaluation of improvements in current sharing service offerings, we found that validation of host's information from external sources (mean = 5.40), enhanced safety in payment systems (mean = 5.35), enhanced privacy regarding personal information (mean = 5.23) and better insurance for shared assets (mean = 5.12) were all considered as important improvement areas. The possibility of paying with cryptocurrencies in sharing services is not considered an important improvement area (mean = 1.63). While most respondents agree (i.e. SD < 1) on the value of good reputation, easy and secure payment systems and effortless communication, all other parameters show standard deviations clustered around +/- 1.5.

Table 12 Descriptive statistics regarding improvements

Improvement Area	**N**	**Mean**	**Std. Deviation**
Host Attractiveness Measurements (7 pt. Likert scale)			
A good reputation	379	6.55	0.90
Easy and secure payment systems	379	6.54	0.84
Effortless communication	377	6.21	0.96
Solid insurance schemes	377	5.51	1.49
A low price	378	5.32	1.36
Detailed information on the host	377	5.02	1.69
Similar personalities	377	2.92	1.57
Improvements of Current Offerings (7 pt. Likert scale)			
Verification of the host's information from an external source	321	5.40	1.41
Enhanced safety in relation to payment systems	320	5.35	1.64
Enhanced privacy regarding sharing personal information	322	5.23	1.61
Better insurance for the assets being shared	319	5.12	1.52
Possibilities for paying with cryptocurrencies	319	1.96	1.48

As an ad-on to the most obvious areas for improvement, we analyzed what information customers are most interested in getting insights to in relation to the host they are renting an apartment form. The intent of this question was to discover how hosts could customize their profile to accommodate customer needs. These results are presented in Table 13, and show that the most valuable information is reviews from other guests (mean = 6.71) and verified ID (mean = 5.99), in addition to their full name (mean = 5.85), language (mean = 5.49), reviews from other sharing platforms (mean = 5.40) and average response time (mean = 5.23). We could also observe that employment record (mean = 2.61), education (mean = 2.44), relationship status (mean = 2.12), political orientation (mean = 2.02) and netflix history (mean = 1.48) ranks well below average (=4.12). By looking at the standard deviations, we are able to identify where our respondents are disagreeing. With a s SD of 0.67, reviews from guests is the metric that the show most consistency, and thus agreement. The same goes for Netflix history, with a SD of 0.97. The remaining metrics have a SD greater than 1, and the hometown of the host (SD = 2) is the metric where respondents shows the highest level of disagreement.

Table 13 Descriptive statistics regarding improvements

	N	Mean	Std. Deviation
Reviews from guests	378	6.71	0.67
Verified ID	376	5.99	1.40
Full Name	379	5.85	1.62
Language	373	5.49	1.39
Reviews from other sharing platforms	377	5.40	1.77
Average response time	373	5.23	1.37
References	375	4.77	1.81
Personal description	375	4.62	1.66
Hometown	374	4.57	2.00
Picture	369	4.57	1.86
Criminal record	376	4.52	1.97
Social media accounts	376	3.43	1.92
Personal Characteristics	371	3.29	1.63
Credit check	374	3.19	1.86
Employment record	375	2,61	1,57
Education	373	2.44	1.44
Relationship status	375	2.12	1.40
Political orientation	372	2.02	1.31
Netflix history	373	1.48	0.97

5.3 Preliminary Bivariate Correlation Analysis

The results from the bivariate Pearson correlations (r) are displayed in Table 14. The same factors will be used in our SEM analysis later on, and the abbreviations found in the model (presented in Section 5.4.1, Figure 12) are listed in the second column of the table.

Table 14 Results of Pearson r correlation analysis

Factor	Abbreviation (SEM)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Innovation Orientation	Innovation															
2. Technology Sceptisim	TechScept	-.38**														
3. Trust Orientation	Trust	.44**	-.29**													
4. Crypto Adoption	CryptoAd	.35**	-.27**	.06												
5. Host Service	HostService	.15*	.04	.19**	.02											
6. Platform Service	PlatService	.01	.28**	-.22**	.19**	.40**										
7. HomeSharing	HomeSharing	.26**	-.19**	.31**	.20**	-.04	-.21**									
8. Uber	Uber	.19**	-.07	.12	.11	-.01	-.15*	.37**								
9. Experience	Experience	.33**	-.16*	.38**	.08	.11	-.15*	.32**	.19**							
10. Data Sceptisim	DataScept	-.12	.16*	-.16*	-.03	.12	.42**	-.14*	-.24**	-.13*						
11. Price	Price	.21**	-.11	.17**	.11	.25**	-.00	.05	.05	.01	-.01					
12. Age	Age	-.09	.12	-.02	-.13*	-.06	.06	-.05	-.31**	.03	.23**	-.27**				
13. Gender	Gender	-.18**	.25**	-.10	-.25**	.31**	.23**	-.12	-.11	-.04	.21**	.00	.05			
14. Income	Income	-.13*	.08	-.09	-.05	-.10	.08	-.10	-.15*	.02	.14*	-.24**	.64**	-.06		
15. Education	Education	.07	-.11	.16*	.06	.03	-.08	.05	.09	.14*	-.03	.09	-.06	-.05	-.15*	

*Correlation is significant at the 0.05 level (2-tailed)
**Correlation is significant at the 0.01 level (2-tailed)

A significant correlation is observed between Trust Orientation and Innovation Orientation (r = .44, p < .01). Furthermore, moderate correlations exist between Data Scepticism and Platform Service (r = .42, p < .01), showing that those who are sceptical towards sharing services utilizing their personal data are also more interested in platforms improvements (safety, security, insurance). Host Service and Platform Service (r = .40, r < .01) shows a moderate correlation, implying that people who perceive Host Service (high reputation, effortless communication, simple and secure payment systems) as critical for Host Attractiveness in home-sharing without a centralized intermediary also value platforms improvements. Moreover, HomeSharing shows a small positive correlation with Innovation Orientation (p = .26, p < .01) and Crypto Adoption (p = .20, p < .01), and a moderate correlation with Trust Orientation (p = .31, p < .01), which confirms that high frequency in HomeSharing usage is associated with trust in the sharing platform. Crypto Adoption is also positively correlated with Platform Service (r = .19, p = .01), which means that high Crypto Adoption is associated with high interest in improvements regarding security, assurance and privacy.

There are several other significant correlations. The most insightful correlations exist between Gender and Innovation Orientation (r = -.18, r < .01), Technology Scepticism (r = .25, r < .01), Crypto Adoption (r = -0.25, r < 0.01), Host Service (r = 0.31, r < .01), Platform Service (r = .23, r < 0.01), and Data Scepticism (r = .21, r < .01). This shows that women (Gender = 1 indicate men, 2 indicate women) are the most sceptical towards innovation, new technology and data utilization of personal information, least interested in cryptocurrencies and information security, and most interested in both improvements regarding host and platform service. Additionally, Price exhibits a minor negative correlation with Age (r = -.27, p < .01), indicating that low prices are more important to younger respondents. Another finding is that Age is uncorrelated with HomeSharing usage (r = -0.06, non-significant), which in turn gives us no evidence for stating that any age group is more adaptive of Airbnb usage.

5.4 SEM Analysis

This section will describe the development of our structural models, and present the results of the Maximum Likelihood Estimation (MLE). In the development of both our structural models, we followed an approach where we started with a fairly broad spectrum of potential theoretical explanations for a phenomenon, before narrowing the focus of assessment so that a specific theoretical basis can be identified, as suggested by Richter, Sinkovics, Ringle and Schlägel (2016). We also used the preliminary descriptive statistics and correlation analysis to make initial proposals and adjustments in the modification process.

5.4.1 Structural Model I - Assessing HomeSharing Usage

Trust needs to be established if peers are going to participate in online sharing activities (see Chapter 3). This led to the inclusion of Trust Orientation (i.e., trust in sharing platforms) as a potential driver of home-sharing usage. Additionally, as blockchain is emerging as a potential disruptive innovation, we have included the respondents Innovation Orientation (i.e., their attitude towards technological innovations and entrepreneurship) as a potential component of usage. We were also interested in knowing whether the respondents' Crypto Adoption (i.e., interest in cryptocurrencies, cryptography, privacy protection, paying with cryptocurrencies) could affect usage of home-sharing. These three latent variables laid the foundation for our measurement model (seeSection 4.4.2), and formed the initial basis for our first structural model.

In order to assess underlying drivers and characteristics of home-sharing usage, the observed HomeSharing variable (measuring the frequency of use of Airbnb) was included as an endogenous variable, and became the parameter of primary interest in our model. In order to determine drivers of home-sharing use, we included previous experience with sharing services (Experience), use of other sharing services (Uber), as well as exogenous control variables such as age, gender, income and education. These variables were introduced in to our model in an incrementally fashion, which allowed us to assess whether the inclusion provide enhanced the overall fit of the model.

Initially, we established dependency between all constructs to HomeSharing, depicted by a one-headed arrow. Modification indices (MI) were evaluated and implemented to increase the structural model fit. In the course of this process, all the control variables were removed, as they did not show any significant relations towards home-sharing usage. This process led to our first structural model, shown in Figure 12. The observed fit metrics are displayed in Table 15, showing good model fit, while the results from the MLE are given in Table 16 as standardized values.

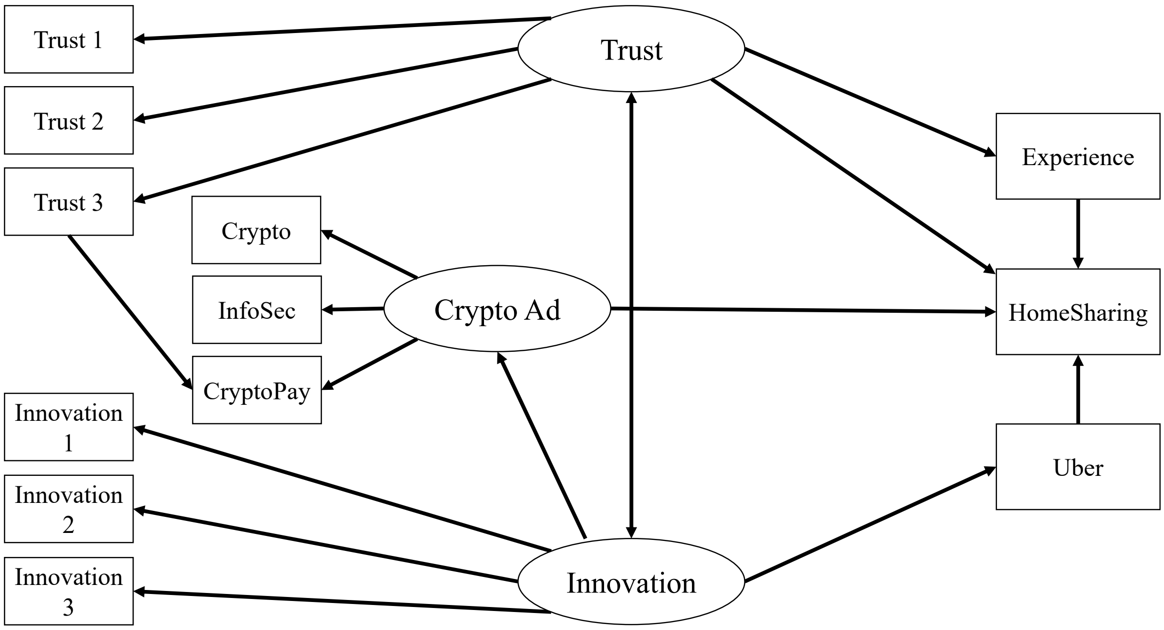

Figure 12: Structural Model-1

Table 15 Goodness of Fit for final Structural Model

Index	**Observed Value**
CFI	0.979
TLI	0.970
RMSEA	0.038
90% Confidence Interval	0.000 - 0.060
Chi-Squared (df = 38)	63.890
p-value	0.051

Table 16 Final Results Structural-Model-1

	Path Coefficient	Std. Err.	P<(z)	R^2	95% CI
HomeSharing				**0.25**	
Experience	0.15*	0.64	0.019		0.03 - 0.28
Uber	0.30**	0.55	0.000		0.19 - 0.41
Trust Orientation	0.20**	0.68	0.004		0.07 - 0.34
CryptoAd	0.17*	0.07	0.016		0.03 - 0.30
Uber				**0.05**	
Innovation Orientation	0.22**	0.07	0.001		0.09 - 0.35
Experience				**0.19**	
Trust	0.43**	0.06	0.000		0.32 - 0.55
Crypto Adoption				**0.62**	
Innovation Orientation	0.40**	0.08	0.000		0.25 - 0.55
Information Security				**0.23**	
Innovation3	0.20**	0.06	0.000		0.08 - 0.32
Crypto Adoption	0.39**	0.07	0.000		0.26 - 0.52
Crypto Pay				**0.43**	
Trust3	-0.26**	0.06	0.000		-0.37 - -0.15
Crypto Adoption	0.64**	0.07	0.000		0.51 - 0.77
	Correlation Coefficient	**Std. Err.**	**P<(z)**		**95% CI**
Trust, Innovation	0.526**	0.06	0.000		0.41 - 0.65

*Significant at 0.05. **Significant at 0.01. CI = Confidence Interval

As shown in Table 16, the strong positive correlation between Trust Orientation and Innovation Orientation found in the Pearson correlation analysis is verified (r = .526, p < .01). Further, usage of Airbnb is related by the usage of Uber (β = .30, p < .01), Trust Orientation (β = .20, p < .01), previous experiences with sharing services (β = .15, p < .05) and Crypto Adoption (β = .17, p < .05). In total, these variables account for 25 percent of the observed variance in HomeSharing, indicated by the R-squared. Among the other interdependencies in the model, we find that Innovation Orientation is affecting the use of Uber (β = .22, p < .01, R-squared = 5 percent), but not the use of Airbnb.

We also observe that Trust Orientation has a strong impact on people's experience with sharing services (β = .43, p < .01), explaining 19 percent of its variance. For the Crypto Adoption constructs, we find that Innovation Orientation is the only existing indicator (β = .40, p < .01), with an R-squared og 62 percent. Among the three indicators in the Crypto Adoption variable, we note that Innovation3 (i.e., I am supportive of entrepreneurial companies) has significant impact on InfoSec (β = .20, p < .01), while Trust3 (i.e., trusting in the institution behind the sharing platform) has negative influence on CryptoPay (β = -.26, p < .01).

The results for the test of indirect and direct effects on the HomeSharing variable is displayed in Table 17. This shows that Innovation Orientation has a significant indirect effect (β = .11, p < .01) on HomeSharing, mediated through the Uber and/or Crypto Adoption variables.

Table 17 Results of Direct and Indirect Relations in Structural Model-1

	Path Coefficient	Std. Err.	P<(z)	95% CI
HomeSharing - Direct				
Experience	0.08*	0.04	0.019	0.01 - 0.15
Uber	0.18**	0.03	0.000	0.11 - 0.24
Trust Orientation	0.16**	0.06	0.000	0.05 - 0.27
HomeSharing - Indirect				
Trust Orientation	0,05*	0.02	0.026	0.01 - 0.09
Innovation Orientation	0.11**	0.03	0.001	0.05 - 0.17

*Significant at 0.05. **Significant at 0.01. CI = Confidence Interval

5.4.2 Structural Model II - Assessing Needs of Improvements

As an elongation to the previous descriptive statistics related to demands for improvements on Airbnb, we developed a second structural model. The basis of this model constitutes of two latent variables: Host service (i.e., measuring the value of high reputation, effortless communication and simple payment systems) and Platform Service (i.e., better insurance schemes, safe payment systems and privacy protection), as described in Section 4.4.2. Additionally, Price Service (i.e., low price offerings) and Crypto Pay (i.e., possibilities for paying with cryptocurrencies) were introduced as single-item indicators for improvements. Consequently, our model analyzed four different areas for improvements.

This model aims uncover how different improvement areas are correlated, as well as investigate whether the demands for improvements differ along any demographic characteristic (age, gender, income and education), interest areas (interest for cryptocurrencies and information security, scepticism towards sharing personal data) or experiences with sharing services (use of Airbnb and previous experiences). We initially included the following single-indicator variables in our structural model: Crypto, InfoSec, DataScept, HomeSharing, Experience, Age, Gender, Education and Income, all with dependency (one-headed arrow) towards the four improvement variables. The process of establishing the model followed the same procedure as with Structural Model-1, removing all non-significant relations and evaluating MIs and implementing changes to increase structural model fit. The final Structural Model-2 is displayed in Figure 13. The observed goodness of fit metrics are given in Table 18, showing good model fit. The results from the MLE are found in Table 19.

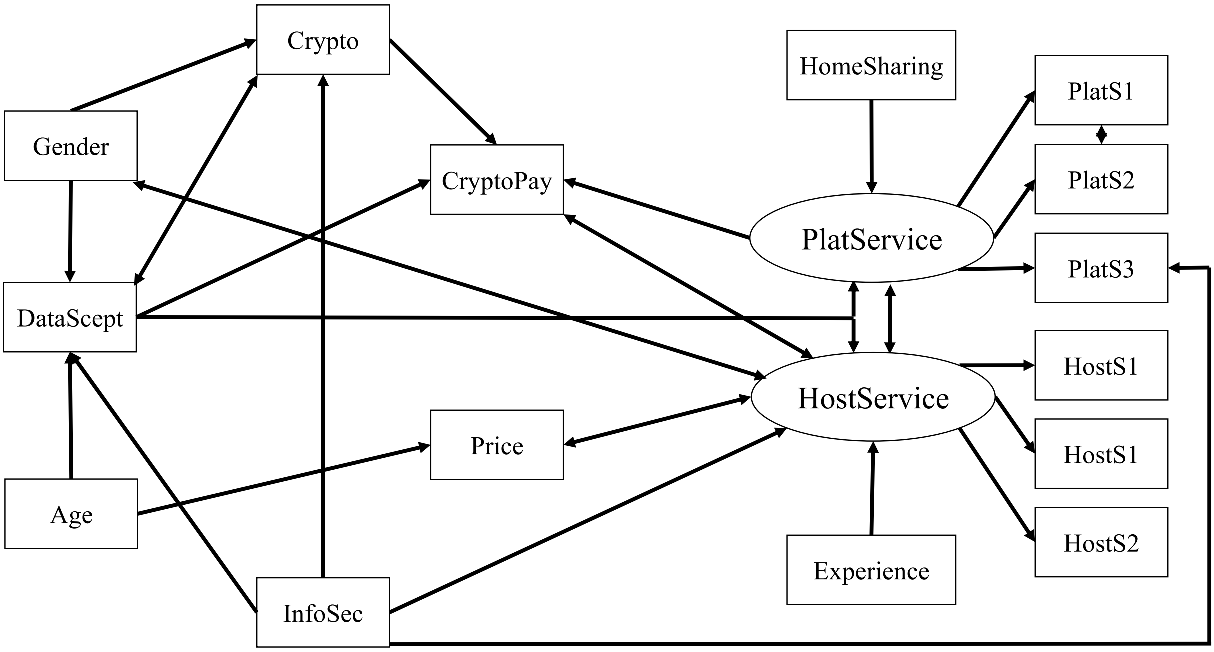

Figure 13: Structural Model-2

Table 18 Goodness of Fit for final Structural Model-2

Index	**Observed Value**
CFI	0.966
TLI	0.953
RMSEA	0.037
90% Confidence Interval	0.016 - 0.054
Chi-Squared (df = 68)	94.135
p-value	0.020

Table 19 Final Results Structural-Model-2

	Path Coefficient	Std. Err.	P<(z)	R^2	95% CI
PlatService				**0.41**	
DataScept	0.59**	0.06	0.00		0.47 - 0.71
HomeSharing	-0.22**	0.07	0.00		-0.34 - -0.09
HostService				**0.19**	
DataScept	0.14*	0.07	0.04		0.01 - 0.27
Experience	0.21**	0.06	0.00		0.09 - 0.33
InfoSec	0.15*	0.06	0.02		0.03 - 0.28
Gender	0.31**	0.06	0.00		0.19 - 0.43
PriceService				**0.07**	
Age	-0.26**	0.05	0.00		-0.37 - -0.16
CryptoPay				**0.29**	
DataScept	0.18**	0.05	0.00		0.08 - 0.28
Crypto	0.54**	0.04	0.00		0.46 - 0.63
PlatS3 - Privacy				**0.52**	
PlatService	0.62**	0.05	0.00		0.52 - 0.72
InfoSec	0.34**	0.05	0.00		0.25 - 0.43
DataScept				**0.12**	
InforSec	0.11*	0.06	0.04		0.00 - 0.22
Age	0.22**	0.05	0.00		0.12 - 0.33
Gender	0.24**	0.05	0.00		0.13 - 0.34
Crypto				**0.28**	
InfoSec	0.34**	0.05	0.00		0.24 - 0.43
Gender	-0.38**	0.05	0.00		-0.47 - -0.29
	Correlation Coefficient	**Std. Err.**	**P<(z)**		**95% CI**
PlatS1, PlatS2	0.37**	0.06	0.00		0.24 - 0.49
PriceService, HostService	0.27**	0.07	0.00		0.14 - 0.40
DataScept, Crypto	-0.19**	0.06	0.00		-0.31 - -0.08
CryptoPay, PlatService	0.22**	0.08	0.01		0.06 - 0.39
CryptoPay, HostService	-0.18*	0.07	0.01		-0.32 - -0.04
PlatService, HostService	0.44**	0.10	0.00		0.25 - 0.63

*Significant at 0.05. **Significant at 0.01. CI = Confidence Interval

As shown in Table 19, the positive correlations between Platform Service and Host Service (r = .44, p < .01), and Host Service and Price Service (r = .27, p < .01) verify the results obtained from the Pearson correlation analysis. Additionally, we find a moderate positive correlation (r = .37, p < .01) between PlatS1 (i.e., increased safety in payment systems) and PlatS2 (i.e., better insurance schemes for shared assets). Moreover, a small positive correlation exists between CryptoPay and Platform Service (r = .22, p < .01), while the opposite trend is found in relation to CryptoPay and Host Service (r = -.18, p < .05), which shows that individuals who are not interested in paying cryptocurrencies asses Host Service (i.e., high reputation, effortless communication, simple payment systems) as the most important area for improvement.

The path-coefficients tell us that Platform Service is affected by DataScept (β = .59, p < .01), and HomeSharing (β = -.22, p < .01), which accounts for 41 percent of the variance in the Platform Service variable. This result shows that the demand for increased safety, insurance and payment systems are considered as most important for those who have (1) have less experience with sharing services, or (2) those sceptical towards sharing personal data. The resulting relationships with Host Services portrays a quite different picture than its counterpart Platform Service, where gender exhibit the highest path coefficient ($\beta = .31$, $p < .01$), telling us that women value Host Service improvements more than men. Also Experience ($\beta = .21$, $p < .01$), InfoSec ($\beta = .15$, $p < .05$) and DataScept ($\beta = .14$, $p < .05$) influence the value of Host Service. These four indicators describe 19 percent of the variance in the Host Service variable.

The only indicator influencing Price is Age ($\beta = -.26$, $p < .01$, R-squared = 7 percent), showing that younger consumers value lower prices. For CryptoPay, both Crypto ($\beta = .54$, $p < .01$) and DataScept ($\beta = .18$, $p < .01$) has a significant impact, explaining 29 percent of CryptoPay's variance.

Another interesting finding is found in relation to the negative relationship Crypto and Gender ($\beta = -.38$, $p < .01$) and InfoSec ($\beta = .34$, $p < .01$). This shows that that men, and those with an interest in information security (cryptography, privacy protection, data criminality) are also most excited about cryptocurrencies. DataScept is positively affected by both Gender ($\beta = .24$, $p < .01$), and Age ($\beta = .22$, $p < .01$). This shows that older women are most sceptical towards data utilization.

To investigate indirect relationships, we performed a test on all four of the improvement variables (see Table 20). We found that Age ($\beta = .08$, $p < .01$) and Gender ($\beta = .19$, $p < .01$) indirectly affects Platform service, mediated through DataScept. We could also observe that InfoSec ($\beta = .19$, $p < .01$), Gender ($\beta = -.48$, $p < .01$), and Age ($\beta = .05$, $p < .01$) indirectly influences the demand for cryptocurrency payments, mediated through Crypto or DataScept.

Table 20 Results of Direct and Indirect Relations in Structural Model-2

	Path Coefficient	Std. Err.	P<(z)	95% CI
Direct:				
PlatService				
DataScept	0.22**	0.04	0.00	0.15 - 0.29
HomeSharing	-0.17**	0.06	0.00	-0.28 - -0.06
HostService				
DataScept	0.05*	0.02	0.04	0.00 - 0.10
Experience	0.09**	0.03	0.00	0.04 - 0.14
InfoSec	0.06*	0.03	0.02	0.01 - 0.12
Gender	0.40**	0.09	0.00	0.22 - 0.59
CryptoPay				
DataScept	0.15**	0.04	0.00	0.07 - 0.23
Crypto	0.43**	0.04	0.00	0.35 - 0.51
Indirect:				
PlatService				
InforSec	0.03	0.01	0.06	0.00 - 0.06
Age	0.08**	0.02	0.00	0.03 - 0.13
Gender	0.19**	0.05	0.00	0.08 - 0.29
HostService				
InfoSec	0.01	0.00	0.15	0.00 - 0.02
Age	0.02	0.01	0.07	0.00 - 0.04
Gender	0.04	0.02	0.07	0.00 - 0.09
CryptoPay				
InfoSec	0.19**	0.03	0.00	0.13 - 0.25
Age	0.05**	0.02	0.01	0.01 - 0.09
Gender	-0.48**	0.10	0.00	-0.68 - -0.29

*Significant at 0.05. **Significant at 0.01. CI = Confidence Interval

6 Discussion

In light of the literature review in Chapter 3 and the results from our quantitative analyses in Chapter 5, this chapter presents a discourse on our research questions. The discussion will consist of three main elements. In Section 6.1, we use empirical findings presented in Chapter 5 to answer our four first research questions. Next, based on both our literature review and empirical insights, we reflect on our last two research questions in Sections 6.2 and 6.3.

6.1 Empirical Analyses

In the following sections, we discuss RQ1-RQ4 based on results from the Airbnb analysis (see Section 5.1), and descriptive and inferential statistics from our consumer survey (see Section 5.2-5.4). We present our interpretations of the empirical findings and how they relate to previous research within similar subjects. We will further discuss the most important results through the lenses of trust evolvements and the disruptive innovation framework in Sections 6.2 and 6.3.

6.1.1 What can previous developments in prices, listings and availability on Airbnb tell us about the market potential for blockchain-based home-sharing platforms?

To summarize our results presented in Section 5.1, all analyzed measurements (price, listings and availability) indicate growth in home-sharing services; number of listings increased by 20.47 percent, average availability decreased by 18.24 percent and average rental prices increased by 2.43 percent. The rapid growth of listings in combination with increased occupancy rates is intriguing clearly suggests high consumer demand, and in turn an unsaturated market for short-term accommodation. These results correspond well with findings put forward by Vaughan and Hawksworth (2015), who predicted a growth of 31 percent in peer-to-peer home-sharing revenues between 2014 and 2025.

The overall positive picture is further enhanced by our survey findings, where 91 percent of the respondents had previously used a sharing service, and 54 percent had booked a listing trough Airbnb during the past two years. These numbers stand in sharp contrast to statistics put forth by Statista (n.d.a), which states that only 3 percent of the Norwegian population were active users of Airbnb in 2015 (11 percent if you include passive users who have signed up to the platform). In turn, there is evidence for a tremendous growth in Norwegian Airbnb users.

Our findings from the Airbnb analysis show substantially higher growth in occupancy rates in Europe compared to North America. This tendency resonates well with growth measures from Statista, predicting that the number of home-sharing users (e.g., Airbnb, HomeAway) in Europe will increase by 34 percent from 2016 to 2020 (Statista, n.d.b), compared to 24 percent in North America (Statista, n.d.c). This suggest that the consumer adoption in Europe is experiencing a more rapid growth than in North America, which might represent attractive market opportunities for new entrants.

Nevertheless, while our analysis shows a favorable prospect for the future growth of the home-sharing market, San Francisco and Barcelona deviate from the average growth in number of listings and occupancy rates. The underlying cause was identified as restrictions imposed by governments. As Airbnb still is a rather new and rapidly growing phenomenon, regulators are just recently getting to grips with the movement and are tightening up the surrounding governance. In 2016, the government in San Francisco imposed regulations on Airbnb users, stating that hosts need to register within the city and obtain a business license in order to be eligible for short-term rentals (Weise, 2017; Airbnb, n.d.e). Additionally, hosts in San Francisco are now only permitted to rent out their permanent residence, restricting them to one rental-unit. Similar developments are found in Barcelona, where the City Council has imposed strict regulations on Airbnb users to manage tourism in its most popular neighborhoods (Burgen, 2017). In March 2016, the city enforced a complicated set of licensing restrictions, stating that all households need a license in order to be eligible for offering short-term rentals. However, as of June 2017, only 9,000 of the approximately 16,000 short-term rentals had obtained such a license. In effect the City Council has employed a team of inspectors aiming to seek out and shut down illegal rentals (Burgen, 2017)

The downturn for Airbnb in San Francisco and Barcelona clearly illustrates a critical aspect of the market for home-sharing; with growth and acceptance, risk and regulatory attention follows. In such, our study supports the regulatory uncertainty of the home-sharing market put forward by several scholars (e.g., Rauch & Schleicher, 2015; Oskam & Boswijk, 2016). It is evident that supply of shared accommodation and short-term rentals is strongly sensitive towards future regulations, positioning regulations as the most significant barrier to future growth in the home-sharing market. However, while our results show a significant market growth between 2016 and 2017, they are inconclusive in making relative yearly evaluations. For instance, research from Morgan Stanley (2017), based on an online survey of 4,000 American, British, French and German consumers, show that even though usage of Airbnb rose 3.3 percentage-points between 2016 and 2017, it was still a downturn from the 7.9 percentage-point growth observed between 2015 av 2016. According to Morgan Stanley (2017), the source of this stagnation is associated with the year-over-year decline in consumer awareness. Although this growth is positive, and consumer awareness reached an all-time high of 80 percent in 2017, consumer-driven adoption is seemingly flattening, and Morgan Stanley (2017) suggests it has reached a level where there is limited incremental upside.

In relation to prices, a deviation from the average increase is found in New York, despite increased number of listings and decreased availability. This combination should imply increase demand for short-term accommodation, and in effect increased rental prices. However, hotel rates in New York grew by 50 percent in the same time period (from first quarter to fourth quarter of 2016) (Statista, 2018b), and the American lodging industry experienced a 3 percent growth in revenue per available room (Statista, 2018c). Hence, our results for New York, in combination with the measures from Statista, stand in sharp contrast to the previous findings of Zervas, Proserpio and Byers (2016), indicating that 1 percent increase in Airbnb listings would decrease hotel revenues by 0.05 percent. This could relate to macroeconomic differences and also regulatory issues imposed on Airbnb operations in New York, for instance restrictions regarding advertisement (Airbnb, n.d.f). Licensing restrictions often serve the interests of incumbents by limiting competition (Stigler, 1971), which could lead to an unfortunate development for home-sharing, as the incentives of city governments and sharing economy firms are often aligned (Cannon & Summers, 2014). Nevertheless, it could also be another indicator of a tipping point regarding the exclusively positive growth within the home-sharing market. As the Morgan Stanley report suggests, it appears that Airbnb have exhausted most of the easy growth, namely the growth resulting from people who would use home-sharing if they knew about it. Hence, although our results imply that there exist an unsaturated market for home-sharing, there seems to be an uncertain development with regards to Airbnb's future growth, due to regulatory issues and stagnation of awareness-driven adoption.

6.1.2 What are the underlying drivers of home-sharing usage?

The underlying drivers of the emergence and growth of the sharing economy has been addressed by numerous scholars (e.g., Hamari et al., 2015; Gansky, 2010; Botsman & Rogers, 2010; Bardhi & Eckhardt, 2012; Kaplan & Haenlein, 2010; Tussyadiah & Pesonen, 2016), who identify technological possibilities, sustainability concerns, social benefits, access to better and cheaper products, enhanced variety and economical gains as the most prominent drivers of growth. However, our intent is not to further support these findings, but to explore whether any user-characteristics can explain why some people tend to use sharing service more than others.

Our preceding analysis (see 6.1.1) found that Airbnb experienced a substantial growth between 2016 and 2017. However, with an average of 1-3 bookings during the past two years for our respondents (corresponding to between 2.7 to 8 million bookings for the Norwegian population[17]), our survey shows that the percentage of Airbnb-bookings in Norway is modest compared to the 115 million short-term rentals booked in 2017 (SSB, 2017b). This clearly suggest that home-sharing is not the preferred accommodation option for Norwegian travellers, but it still accounts for a remarkable portion of the short-term rental options.

According to Moore (2014), when new technological innovations are introduced to the market, they are not adopted by all the individuals in the social system at the same time. Instead, they initially attract a lot of attention evoke enthusiasm from a small crowd of *innovators* and *early adopters*, who are able to envision the underlying potential and accept the associated risks. These groups often consist of younger, educated people who have more financial lucidity than those who adapt the innovation later on (Rogers, 1962). Consequently, as the adoption of Airbnb in Norway is relatively recent (see6.1.1), we expected that demographic differences would enable us to distinguish a cluster of early adopters. However, this was not the case – neither age, income nor education showed a significant impact on use of Airbnb, which in turn implies that Airbnb has moved on to the mainstream market. This stands in contrast to Olson (2013), who show that consumers with higher income levels are more active users of home-sharing, and John (2013), suggesting that younger demographics are more likely to participate in the sharing economy.

[17] 5.3 million people live in Norway as of 1st quarter 2018 (SSB, 2018).

However, our results are to some extent consistent with a similar study conducted by Tussyadiah and Pesonen (2016), who found no significant differences in terms of gender and age between users and non-users of home-sharing in the United States, although they did find significant differences in terms of education and income, indicating that educated consumers with higher income (i.e., typical high-end users) were more frequent users of Airbnb. The latter finding supports our indication of mainstream adoption, as the service is no longer solely attractive to the low-end segment. In such, our results also support Nwonu (2017), who states that sharing economy business models are currently trending and evolving due to socio-cultural changes.

Moreover, the association between trust in sharing services and a general positive attitude towards innovations is evident. Still, what is more intriguing is that while level of trust in sharing services (i.e., Trust Orientation) does impact home-sharing usage, the level of innovation orientation does *not*. However, Innovation Orientation does impact usage of Uber, which is expected as Uber is a more foreign concept due to a series of regulatory and legal issues in Norway (see Farr, 2017). With this further support, it seems evident that the concept of home-sharing has matured as a mass-market alternative for short-term accommodation, and in turn has fully disrupted the existing industry as also suggested by Christensen, Altman, McDonald and Palmar (2016).

Nevertheless, amongst those who have participated in the sharing economy, the general experience among Norwegian consumers are positive, and our results imply that good experiences is a critical driver for Airbnb usage. Closely related to this finding, we observe that use of Uber is the parameter that is most closely related to use of Airbnb. These results clearly suggest that the most effective driver of Airbnb usage is good experiences from previous sharing economy transactions, and experiences from other sharing services. This is supported by Newman and Antin (2016), the Head of Data Science and Research in Airbnb respectively, arguing that retention (i.e., the likelihood that a guest or host uses Airbnb more than once) is a critical element for continued use of home-sharing services. They also suggest that while retention is not a direct measure of trust, there is a general tendency that use of Airbnb increase when the levels of trust increase. This hypothesis is confirmed in both our correlation and SEM analysis, where the significant relation between trust and use of Airbnb was observed. Hence, it becomes evident that designing for trust is key for the continued success of home-sharing platforms.

Botsman (2016) argues that distributed trust needs to be established through three different layers, referred to as climbing *the trust stack*. The first layer is related to trust in the idea. For Airbnb, the idea consists of renting a stranger’s house when traveling. Considering that Airbnb seems to have reached mainstream adoption, it becomes clear that people are trusting the idea. The second layer relates to trust in the company; can Airbnb effectively manage the interactions and transactions and mitigate the associated risks? Our results showed that consumers generally place high levels of trust of the institution behind the sharing platform, which in turn shows that they have climbed the second layer of the trust stack. Lastly, the third layer is concerned with trust in the individual you are interacting with. In the case of Airbnb, trust is established through reputation systems. However, while our results suggest that people place a considerable amount of trust in the strangers they transact, their trust in the sharing platform (e.g., Airbnb) is still notably higher. In effect, our results do not distinctly support the lack of trust in institutions identified in Section 3.2. On a different note, we found that the interest for paying with cryptocurrencies on sharing platforms is negatively affected by trust placed in the institutions (e.g., Airbnb). Hence, our results support the proposition suggested in Chapter 3.2 (e.g., from Tapscott & Tapscott, 2016), implying that lack of trust in institutions is fostering the interest and adoption of decentralized alternatives.

Nevertheless, as Newman and Antin (2016) state: "Not long ago our friends and families thought we were crazy for believing that someone would let a complete stranger stay in their home." Consumers have already made a large trust leap by using sharing services and trusting the reputational mechanisms. Hence, while our results do not entirely support that trust in institutions is being replaced by trust in strangers, they still indicate that people are trusting towards both institutions *and* strangers on sharing platforms. And this might provide fertile ground for the envisioned trust shift put forward by Botsman (2017).

As was reasonable to expect, consumer's innovation orientation has a strong positive effect of Crypto Adoption, in addition to the two being notably correlated. Still, our results show that on one hand, the amount of consumers interested in cryptocurrencies are scarce, while on the other hand, a substantial amount reported to be interested in information security. This suggests that while information security (i.e., privacy protection, cryptography and data criminality) is an important area of consumer interest, few are turning their attention towards the decentralized opportunities that exist. This indicate that the "crypto-community" is still limited, and in turn confirm our findings from the project thesis, indicating that those interested in cryptocurrencies and decentralized application could be characterized as early adopters (Boge & Nyrønning, 2017). Nevertheless, what is more exciting is that when people indeed do have a high Crypto Adoption, it also positively impacts their usage of Airbnb, showing that the most frequent users might be those having the highest interest in cryptocurrencies and information security. Especially when considering that no other personal characteristics such as age, gender, income and education neither had significant impact nor correlation with Airbnb usage, this could indicate that the most innovation oriented users are still amongst those with most frequent use.

6.1.3 What are the customer demands for improvements in home-sharing platforms, and how can blockchain technology be deployed to serve these needs?

While our study shows that people in general have good experiences with sharing services, it also reveals that there exist several unmet needs (see Table 12, Section 5.2.2). Information verification, safety in payment systems, privacy regarding personal data and insurance for shared assets were identified as areas of improvements. Our inferential analysis further show that these improvement areas are most important to those who are skeptical towards sharing personal data and having lower frequency of home-sharing usage. Furthermore, one of the most visible forces of security concerns is the notable negative correlation between Data Scepticism (i.e., attitude towards sharing utilization of personal data) and use of Airbnb and Uber, indicating that privacy concerns still propose an obstacle for more frequent use of sharing services. This is in line with findings from Wallenstein and Shelat (2017), who found that users refrain from using sharing activities because they are uncomfortable with sharing personal payment information, and Morgan Stanley (2017), who argue that privacy and safety are the main barriers to initial adoption of sharing services They suggests that improvements within these areas are considered attractive among both consumers and non-consumers.

In addition to the aforementioned improvement areas, the respondents were asked what attributes would be most valuable for host attractiveness if they were going to consider engaging in a home-sharing transaction without the presence of a trusted intermediary (see Table 12). Here we found that the respondents perceive a good reputation and easy and secure payment systems as the most important factor for engaging in such a transaction, followed by effortless communication. Furthermore, it is worth mentioning that our inferential statistics revealed that the importance of host-related features (i.e., high reputation, effortless communication, simple payment) is mainly driven by gender and experience, indicating that women with good experiences value these attributes the most. Hence, this stands in contrast to the indicators of platform improvement (i.e., security, safety, privacy), where low frequency of home-sharing use and data scepticism were the most dominant influences. This is in accordance with findings from Varma et al. (2016), who found that travelers with safety and security concerns would always pick hotels over Airbnb listings. This could indicate that host-attractiveness first becomes essential when you become an active user.

A good reputation is the most valuable metrics for host attractiveness (see Table 13, section 5.2.2). This was expected, considering the importance of review and rating systems previously discussed. This is supported by Zhu and Zhang (2010), who argue that peer evaluations are useful sources of information, as it reduces uncertainty and facilitates the decision process. However, Zervas, Proserpio and Biers (2015) found that 95 percent of the reviews on Airbnb have a rating of 4.5 out of 5 stars. Hence, one could question the differentiating importance of reviews, as almost every user leaves top-ratings. This could of course indicate that "all hosts perform excellent". However, a more likely explanation is found in Zervas et al. (2015) and Horton and Golden (2015), who suggests that there exist an inflation in the reputation system because hosts can use various strategies to avoid negative reviews. Additionally, reviews from other sharing platforms (e.g., Uber, Homeaway or Finn.no) are considered important sources of information about the host, indicating that implementing mechanism that enables cross-reputation between platforms could enhance guests' evaluation of trustworthy and attractive hosts.

Furthermore, verified ID, full name, language and average response time were considered as valuable information. In contrary, a picture of the hosts, their criminal records and social media profiles are considered less important, which is contrary to the findings of Ert et al. (2016), suggesting that trustworthiness of a host is mainly inferred from their profile pictures. Moreover, Kamal and Chen (2016) found that a background check of the criminal records was the most important security measure to increase the likelihood of participating in the sharing economy. Kamal and Chen (2016) also found that 76 percent of their respondents considered access to the user's profile on social networks would increase their levels of trust in the transaction. Moreover, we find that users value information about the hosts behaviour on the sharing platform (i.e., reputation, response time and communication) more than his personal information (e.g., relationship status, education, social media account). This suggest that consumers place a high level of importance on platform facilitated trust mechanisms.

Another intriguing result is found in relation to the importance of low price offerings. Several researches have emphasized that sharing services primarily surfaced as consumers became more attentive to their spending habits in the wake of the financial recession, making the collaborative consumption an appealing alternative for consumers because of its economic benefits (e.g., Botsman & Rogers, 2011; Bardhi & Eckhardt, 2012; Guttentag, 2015). However, our findings show that low price offerings score lower than both solid insurance schemes, effortless communication, a good reputation and secure payment systems. Hence, this strengthens our argument of Airbnb having reached mainstream adoption, and indicate that trust-facilitating mechanisms are more important than economic benefits. This is in line with Gefen (2000), who argue that without the presence of trust, individuals would rather refrain from online interactions than evaluating potential outcomes.

By drawing from the overview of blockchain attributes and the technological representation of blockchain technology in Sections 3.3 and 2.1, respectively, we provide further insights as to how the technology can enhance identified improvement areas of sharing services in Table 21. We refer to the rightmost column of the table for further readings on the presented subjects.

Table 21 Improvement of sharing services through blockchain technology

Improvement area	How can blockchain solve it?	Further readings
1. Verification of the hosts information from an external source	1. Blockchain and identity verification can be combined to create a digital ID that can act a digital watermark in every online transaction. Consequently, there is no uncertainty regarding whether the transacting person is who he says he is. 2. Blockchain-based identity management platforms can validate digital identities, birth certificates, passports and so forth from third-party sources. And as information on the ledger is unchangeable, personal information is legitimized. 3. Blockchain technology can enhance reputation management, allowing for users to transfer their reputation across different platforms. Hence, it will give users a better overview of the peer they are transacting with.	Medici (2017), Swan (2015)
2. Enhanced safety in relation to payment systems	1. The transactions are validated through consensus, which means that no fraudulent transactions are able to pass through the network. 2. Rapid and cheaper payments due to no delays or fees in centralized intermediaries. 3. Coins can be stored in off-chain servers to further increase safety. 4. Transactions are settled peer-to-peer without passing through a centralized server or institution. Hence, there is no central points of failure.	Nakamoto (2008), Catalini & Gans (2016)
3. Enhanced privacy regarding sharing personal information	1. The blockchain does not need to know who its users or nodes are, and participants are not obligated to provide personal data in order to access the (public) blockchain. In effect participants can maintain an anonymous profile, which makes it virtually impossible to connect actions to identities. 2. Transactions across the blockchain network requires both a private and a public key. As the individual users are in control over their private keys, they are able to control and select what, how much and when they share their information. 3. Data is not stored on a centralized servers, which reduces the risk of hacker attacks and centralized data utilization	Tapscott & Tapscott (2016), Zyskind & Nathan (2015)
4. Better insurance of assets being shared	1.Assets can be registered on the blockchain (i.e., smart assets), and its actions can be governed through a smart contract (i.e., smart lending). Consequently, in the case of potential wrongdoings in a home-sharing exchange, the outcome is already predetermined by the code.	Swan (2015), Siddiqi (2017)

6.1.4 Which customer segments present attractive targets for blockchain-based home-sharing platforms?

In line with our findings in 6.1.1 - 6.1.3, prices in the Airbnb market are rising, and home-sharing as a phenomenon has gained immense traction and is suggested to have reached mass-market adoption. On their way, Airbnb have heavily nurtured the self-reinforcing dynamic of network effects (Jorgenson, 2015), which currently seems to be leading the home-sharing industry towards a "winner takes all" market (see e.g., Eisenmann, Parker & Van Alstyne, 2006; Rysman, 2009). In light of this, initially targeting the mass-market of home-sharing users appears to be an arduous form of market entry for the blockchain-based contenders. In effect, identifying early adopters, and understanding the needs of this customer segment, seems to be key for stimulate the initial platform adoption (Eisenmann et al., 2006; Baldwin & Woodard, 2009), and crucial for the platforms' survival (Allen, 1988).

However, there exist limited literature that emphasize on who the early adopters of Airbnb were. One of the few explorations is conducted by Quattrone, Proserpio, Quercia, Capra & Musolesi (2016), who suggest that early adopters were young and ethnically diverse residents living in central neighborhoods, and likely composed of students due to the negative correlation between Airbnb prices and income. This also resonates well with the findings of low prices as the primary motivation for seeking sharing services (e.g., Guttentag, 2015; Gibbs et al., 2018; Möhlmann, 2015). This of younger demographics being the early adopters of Airbnb is further supported by significant negative correlation between use of Uber and age, which additionally is more dependent on a high Innovation Orientation than use of home-sharing services (which was more dependent on the trust orientation).

However, according to our results, no demographic stands out as a group of early adopters of home-sharing services in Norway. This relates well to the findings of SSB (2017a), showing that the use of Airbnb in Norway is evenly distributed amongst different age groups, and to similar studies conducted by Volgger, Pforr, Stawinoga, Taplin and Matthews (2018) in Australia, where Airbnb usage also appears to have penetrated the mainstream market. Interestingly, the price of several Airbnb condos[18] are approaching the level of surrounding hotel rates[19]. Hence, based on the demographic characteristics alone, it suggests that home-sharing provide more than just an economical option for travellers, indicating, as previously stated, that home-sharing is no longer solely attractive to the low-end market. However, we identified improvement areas in current offerings, and showed how blockchain technology propose an attractive solution to business model innovation (see Section 6.1.2).

Still, what is intriguing is that low prices (which is made possible with blockchain-based home-sharing due to elimination of several fees) mainly appear attractive to the younger respondents. It should also be noted that considering the characteristics of our respondents, most of these younger demographics are also students or highly educated professionals, which according to Tussyadiah and Pesonen (2016) have greater awareness of value propositions in collaborative consumption. Hence, considering the early innovator characteristics (i.e., younger, educated people) suggested by Rogers (1962), and the findings of Quattrone et al. (2016), it might seem likely that early adopters of Airbnb that are becoming over-served with the current price level offerings.

Furthermore, in relation to cryptocurrency payments on home-sharing platforms, our results show that this improvement is mainly important to those who have an interest for cryptocurrencies. This group primarily consists of men, who also are interested in information security (i.e., cryptography, privacy protection, data criminality). This also relates well to the

[18] Excluding the most extravagant properties (e.g., castles and luxury yachts), and only considering listings that resemble the average hotel experience.
[19] Compared by using the search engine at Airbnb.com and Expedia.com.

findings of gender being negatively correlated with Innovation Orientation, showing that men are most accepting towards innovative solutions. However, what is even more interesting, is that both the CryptoAdoption construct and single-indicator CryptoPay is positively correlated with Platform Service, suggesting that users with an interest for cryptocurrency solutions also assess increased safety, insurance and safe payment systems as important improvements in current sharing services. Moreover, we could observe a small negative correlation between the Crypto Adoption construct and Age, thus enhancing our implication of younger people as likely early adopters. In summation, this suggest that an attractive market segment for blockchain-based home-sharing startups are young, male cryptocurrency enthusiast.

However, our results found that scepticism towards data utilization was the main driver behind increased Platform Service (i.e., improvement that might be made available through blockchain-based home-sharing). And interestingly, the respondents with highest data scepticism are females of a higher age, which indicate that those who could benefit most from blockchain attributes are older women. Recent predictions from PwC (2017) state that 'silver surfers' (i.e., consumers over 50) are the fastest-growing user group for many platforms, including Airbnb. Nevertheless, while such as segmentation strategy would stand in strong contrast to our previous discussion of early adopters and crypto enthusiasts, PwC (2017) still argue that platforms who are successful in capturing this demographic group will gain a competitive advantage against their rivals.

When aiming to steal consumers or potentially disrupt the industry, new technology must exploit the "blind spot" of current market leaders (e.g., Foster, 1986; Henderson & Clark, 1990). Our results indicate that there could exists two niche markets for blockchain-based home-sharing startups; (1) younger men (preferably students) with an interest in cryptocurrencies, and (2) older women with a high scepticism towards utilization of personal data on sharing platforms. And according to Gilbert (2003) and Rafii and Kampas (2002), a latent disruptive business model often diffuses in niche markets outside the incumbent's mainstream market long before it becomes disruptive.

The key theoretical foundation underlying the distinction of high-end and low-end disruption is that high-end innovation results in improved performance, whereas low-end propose improved affordability (Govindarajan & Kopalle, 2006). This also relates well to our findings, suggesting that low-end disruption could be enabled by targeting price-sensitive younger students, and preferably men with a crypto interest, while high-end disruption could be achievable by presenting female 'silver surfers' with the added benefits blockchain-based home-sharing in relation to enhanced privacy, security and safety. However, even though blockchain technology can compete on both price and performance in the home-sharing environment, it risks being "stuck in the middle" if it deploys a low-cost and a differentiation strategy simultaneously (Porter, 1980). Hence, choosing one of the target groups appears to be the wisest choice.

Our correlation analysis revealed that men are more open to technological innovations than women. This is supported by Li, Glass and Records (2008), who found that men move through technology adoption stages more rapidly than females do. Hence, considering that blockchain-based home-sharing startups are commercializing a complex technology, having an innovative enthusiastic target seems beneficial. In such, the segment of younger male students with an interest in cryptocurrencies and information security presents itself as the most attractive customer segment for initial targeting. Interestingly, this corresponds well with the early adopters of CryptoCribs, (see Section 2.3.2.), where approximately 90 percent of the hosts are male in the age range from 25-35 years. Furthermore, Cryptobnb (a similar home-sharing startup) are targeting existing users of home-sharing platforms and a younger demographic of millennials (Kettley, 2017). Additionally, Beenest and CryptoCribs (see Section 2.3) aims to attract the crypto-community. Hence, our results confirm what already established players within the blockchain-based home-sharing market are observing; younger male consumers, familiar with sharing services and an attraction towards the crypto-community present the most lucrative targets.

6.2 How can developments of trust impact the disruptive potential of blockchain technology in home-sharing?

The development of trust and how it influences adoption of blockchain technology is, to the best of our knowledge, mainly addressed by Botsman (2017), Seidel (2018), Piscini, Guastella, Rozman and Nassim (2016) and Hawlitschek el al. (2018). Seidel (2018) points out that the shift towards distributed trust has the potential to displace data giants such as Google, Facebook and Airbnb, whereas Botsman (2017) focus on how the history of trust can be utilized to facilitate an understanding of the major waves of disruption in society. Piscini et al. (2016) briefly touch upon the subject of trust in relation to blockchain technology, but focus on how the underlying technology allows us to discover new and disruptive ways of achieving and applying trust in society. Seemingly, none of these publications explore trust in relation to the disruptiveness blockchain-based startups represent. However, they all seem to agree that a power shift is flourishing through our society, where trust will shift from institutions to individuals, leading us into the age of distributed trust.

In the pre-blockchain society we have to rely on third-party intermediaries and centralized organizations to vouch for strangers, and to maintain and perform transactions and business logic that power commerce online (Tapscott & Tapscott, 2016; Casey, 2016). Intermediaries in the sharing economy, like Airbnb and Uber, exist because people are reluctant to trust strangers. Hance, building trust between two parties comes at a cost of paying a percentage fee to intermediaries like Airbnb and Paypal. Consequently, many of these internet-driven industries are led by a handful of centralized giants, continuously nurturing their network effects. However, our findings clearly show that consumers are sceptical towards private data utilization and are concerned about their privacy, safety and security when using such platforms. In fact, lack of secure payment systems, data security, privacy and transparency are amongst the top drivers of distrust in peer-to-peer markets (e.g., OECD, 2017; Olson, 2013; Botsman & Rogers, 2011).

Our findings suggest that blockchain technology does position itself as a solution that could accommodate many of the demands for improvements in home-sharing services. Moreover, our findings have shown that people put a significant amount of trust in strangers they interact with on sharing platforms, indicating that the promising outlooks of a distributed trust society is also visible amongst Norwegian consumers.

In Section 6.1 we argued that the concept of home-sharing has matured as a mass-market alternative to short-term accommodation. Further, home-sharing services have climbed all three layers of the trust stack introduced by Botsman (2016); consumers are adopting the fundamental ideas of the sharing economy (layer 1), they place trust in both the sharing platform (layer 2), and the peers they transact with (layer 3). In addition, our literature review and empirical findings show a rapid growth in use of home-sharing services and increased acceptance of Airbnb and their business model. These findings support the acclaimed trust shift, thus providing decentralized startups with ample opportunities to enter the home-sharing market. However, despite the emerging trust shift, our findings show that trust in sharing economy institutions is currently rated higher than trust placed in a transacting peer on sharing-service platforms. In other words, the fully distributed trust era presented by Botsman (2017) might still be an utopian idea.

According to the trust stack, blockchain-based startups have overcome the first layer, as consumers have already adopted the idea of home-sharing services. However, consumers still have to trust the platform and the strangers they transact with. One of the core concepts of blockchain technology is that interactions can be predefined, and actions enforced by smart contracts. In such, people or machines can interact without having to trust the other party (Swan, 2015; Wright & De Filippi, 2015), and provides a secure mechanism for honest actors to be properly compensated if transacting peers default or act untrustworthy (Kosba, Miller, Shi, Wen & Papamanthou, 2016). Hence, it essentially eliminates the last layer of Botsman's trust stack, as the technology provides a trusting interface between strangers through increased transparency and consensus validation**.** Hence, with the trust shift facilitating a broader acceptance of home-sharing as a business model, blockchain as a core technology concept in itself function as the last layer of the trust stack. Accordingly, in correspondence with Botsman (2016), we argue that blockchain-based home-sharing is not only disruptive in relation to technological opportunities and innovative business model design, it is also disruptive in the way it allows strangers to trust each other purely through technology. As Marc Andreessen (as cited in Tapscott & Tapscott, 2016), the co-creator of the first commercial Web browser stated: "This is the thing! This is the distributed trust network that the Internet always needed and never had (Alford, 2018)."

According to Botsman (2017), we are currently experiencing a trust vacuum as our confidence in institutions and authorities are called into question, and developers are gradually decentralizing conventional computer systems, with hopes of improving privacy, eliminating authorities and reducing fees (Soska et al., 2016; Einav et al., 2016). And as our results suggest, trust in sharing services is driving both home-sharing usage and consumer's innovation orientation. However, according to Botsman (2016), trust is "a confident relationship with the unknown"; when there exists a gap of uncertainty between the known and the unknown, trust is the ingredient that allows us to take the leap. Hence, for blockchain-based startups, the design of trust, through accommodating unmet needs of privacy, security and safety, presents itself as the key concept that could make or break their disruptive success. Nevertheless, following the fact that trust in businesses and other centralized institutions is at an all-time low (see Section 3.3.2), there could be room for utilizing the shifting trust orientation to further unbundle the conventional trust hierarchies.

When institutional systems vaporize, Botsman (2017) argues that innovations emerge. Blockchain technology might be the missing link in the envisioned trust shift, and as the technology gathers momentum, it also gives hope and space for those aiming for incumbent disruption (Boge & Nyrønning, 2017). As Lundy (2016) argues: "Eliminating the need for an intermediary could impact some of the biggest technology companies. Rather than use Uber, Airbnb or eBay to connect with other people, blockchain technology services allow individuals to connect, share, and transact directly, ushering in the real sharing economy. Blockchain technology is the platform that enables real peer-to-peer transactions and a true sharing economy."

In a sharing economy where we own our identities and personal data, we can transact, create and exchange value without powerful intermediaries acting as the arbiters of money and information, and we can ensure that the creators are compensated for their intellectual property (Tapscott & Tapscott, 2016). However, as Botsman (2017) also emphasizes, we are at the beginning of this new relationship between technology and trust, and we still need to figure out how we shall appropriately design these digitally enabled distributed trust systems. We should also be aware that if we reverse the traditional sources of trust, we are also entering an unknown minefield, which might present us with tremendous challenges. Lemieux (2016) states that the transition to distributed trust systems may present major security concerns, due to the fact that no central organization can be identified and targeted for regulatory enforcements. These concerns became visible during the hacking of the first ever decentralized autonomous organization (The DAO) built on Ethereum smart contracts in 2016. While investors and developers fully relied on "the wisdom of the crowd", a computational loophole led The DAO to be drained for tokens with a market value of $50 millions (DuPont, 2017), which was never recovered.

While many argue that the blockchain consensus mechanism eliminates the need for trust between exchanging peers, others state that distributed ledgers, like blockchain, are not essentially trustless systems. Instead, they move trust to the periphery; despite information on the blockchain being permanent, the individuals providing the information must still be trusted (Evans et al., 2016). Kasireddy (2017) approaches this from a different angle, and suggests that instead of looking at blockchain systems as trustless, it is more accurate to say that blockchains are built on the basis of distributed trust; they allow us to trust all the participants in the network in aggregate, eliminating the need to trust single entities. However, we still need to trust that a majority of the power present in the network are held by stakeholders sharing trustworthy values, which again stresses the importance of 'designing for trust'.

As trust has evolved from institutions to individuals, it has also laid the foundation for distributed systems based on blockchain technology to emerge. Botsman (2016) implies that as this traditional institutional trust framework continues to crumble, it creates fertile ground for technology-engineered decentralised trust between people. For entrepreneurs, this also implies that there exist opportunities for redesigning institutional systems with more transparency, integrity, democracy and accountability. By successfully implementing distributed trust, the previous taken-for-granted centralized organizations will lose their power and importance (Seidel, 2018). Consequently, the real disruption taking place might not only be technological; it is also the trust shift that will open the doors to new ways of designing systems that will change human behaviour on a large scale (Botsman, 2016). As William Gibson once put it (as cited in Maharajh, 2016): “The future has arrived - it’s just not evenly distributed yet”.

6.3 What is the disruptive potential of blockchain technology in the home-sharing industry?

As with all potentially disruptive technologies, there are conflicting views on the innovativeness and real-work applicability of blockchain technology. In order to discuss our final research question, we structure our reasoning in three parts. First, in Section 6.3.1, we address whether blockchain technology is a disruptive innovation. Next, in Section 6.3.2, we explore how blockchain fits in traditional organizational and disruptive business frameworks. Finally, in Section 6.3.3, we discuss the disruptive potential of blockchain-based home-sharing platforms.

6.3.1 Is Blockchain A Disruptive Innovation?

Scholars and industry practitioners argue that blockchain is a disruptive technology (e.g., Crosby, Pattanayak, Verma & Kalyanaraman, 2016; Mattila, 2016; Tapscott & Tapscott, 2016; Cong & He, 2018) with the potential to enable a new set of disintermediated digital platforms (Swan, 2015). However, already in 2004, Danneels (2004) pointed out how the term “disruptive innovation” had become too separated from its theoretical foundation. This view is supported by Christensen et al. (2015), who argues that disruptive theory is in danger of becoming a victim of its own success, as the core concepts are being overshadowed by the popularity of the initial formulation. In effect, disruptive innovation is often used to describe any situation in which an industry is reshaped and previously successful incumbents falter. Consequently, over the past 20 years, the academic discussion regarding a general definition of disruption has been widely debated in academia (e.g., Yu & Hang, 2010; Christensen, 2006; Schmidt & Druehl, 2008; Markides, 2006).

In Chapter 3, we presented attributes of blockchain technology, and in Section 6.1.2 we showed how many of them provide beneficial features for increased customer satisfaction. Moreover, as suggested by Charitou and Markides (2003), Christensen (1997), Christensen and Bower (1996), Christensen and Raynor (2003), Danneels (2004), and Gilbert (2003), disruptive innovations are powerful means for broadening and developing new markets and functionality.

Similar to how the Internet reinvented communication, blockchain may disrupt transactions, contracts, trust, key structures of business, governments and society (Piscini et al., 2016). However, blockchain technology is a relatively new innovation, and no industry has yet been exposed to disruption in the extent suggested by the theoretical conceptualization. As presented in Section 2.3, there are currently only a few real players within the segment of blockchain-based home-sharing, and none of them has matured to such a level that disruption seems achievable at any near point in time. Nevertheless, while these exploratory ideas are still in their infancy, the disruptive effect could be profound. Consequently, Danneels (2004) raises a key question: can the disruptive technology framework be used to make ex ante predictions?

Disruptive innovation theory has been criticized due to its use of historical data, weakening its predictive value (e.g., Tellis, 2006; Danneels, 2004). As briefly introduced earlier, Govindarajan and Kopalle (2006) argue that all prior measures of disruptiveness was indeed made ex post (i.e., based on actual results rather than forecasts). This thus presents a limitation of the theory, as one can only assess the disruptiveness of an innovation after it has been introduced. Moreover, Danneels (2004) argues that despite the importance of disruptive innovations, relatively little academic research has been conducted on the characteristics of such innovations. According to Lepore (2014), the disruptive theory seems to be so widely accepted that its predictive power is rarely questioned.

Hence, how can we predict if a technology will be disruptive? As Doering and Parayre (2000; p. 75) state: "Significant emerging technologies are easily seen 'after the fact', and companies are then congratulated or castigated for their decisions to pursue them or ignore them. But rarely are the winners clear at the outset." According to Danneels (2004), ex ante predictions must include forecasting what performance the market will demand along various dimensions, and what level of performance the innovative technologies will be able to offer. However, Govindarajan and Kopalle (2006) argue that there is no appropriate measure for the disruptiveness of innovations per se, also resulting in a lack of research on the subject. While extrapolating historical performance trends is a seemingly appropriate approach, it is considered very difficult in the case of young technologies, such as blockchain technology, where historical data is limited and future evolution is uncertain (Danneels, 2004).

Christensen (2006) meets the critique by arguing that a theory "must help evaluate a technology after it has been conceived or to evaluate a business venture after it has been proposed or launched". Furthermore, disruptive theory shall provide both incumbents and entrants with helpful predictions about the possible consequences of different actions they take relative to the innovation. Moreover, according to Govindarajan and Kopalle (2006; p. 17), even though the framework "may not help predict ex ante if a technology will be disruptive, the framework helps make ex ante predictions about the type of firms likely to develop disruptive innovations." Also Yu and Hang (2010) conclude that while we are unable to know for certain what the results of different actions might be, disruptive innovation theory can be applied to anticipate the future of firms. Nevertheless, the earlier these predictions can be made after conception of the disruptive technology or innovation, the better (Christensen, 2006). Still, it is important to acknowledge that disruption is a process, and while some potentially disruptive innovations succeed, others will fail. However, according to Christensen et al. (2015), empirical tests show that using disruptive theory makes us measurably and significantly more accurate in our predictions of which fledgling businesses will succeed.

As discussed in Adams (2018), a technology is not intrinsically disruptive. It could be radical, and potentially a component of disruptive innovation, but what ultimately determine disruption is how new entrants or incumbent firms deploy it to achieve or sustain competitive advantage. Even the optimistic advocates of blockchain argue that similar to previously adopted disruptive technologies, there will be beneficial and detrimental aspects of blockchain technologies that must be carefully considered before developing and commercializing new business ideas. Iansiti and Lakhani (2017) emphasize that true blockchain-led transformation is still many years away. They view blockchain as a *foundational technology*, with the potential to create new foundations for our economic and social systems, which differs from the traditional disruptive technologies. Also Kane (2017) and Flament (2017) refrain from defining blockchain technology as disruptive, and instead label it as new *general purpose technology*.

Hence, while it is difficult to label blockchain technology as a disruptive innovation ex ante, blockchain's attributes and its entrepreneurial landscape still mirrors its radical potential. Freidlmaier et al. (2017) argue that the development in upcoming years will reveal if blockchain is merely an incremental innovation – or a truly disruptive technology. In such, we agree with Adams (2018), stating that at this point in time, it is more precise to consider blockchain an *enabling disruptive technology*. Consequently, this again stresses the importance of exploring *how* blockchain-based home-sharing startups could succeed.

6.3.2 Blockchain and Disruptive Theory Applicability

According to Seidel (2018), the majority of organizational theory is based on the fundamental assumption that organizational structures present the best ways to solve certain market-based trust coordination issues, by providing a centralized source of legitimacy. However, while this assumption historically has been considered valid, the emergence of decentralized systems and distributed trust through blockchain technology seems to fundamentally challenge the core tenets of previous organizational theory (Seidel & Greve, 2017). Illustrating it by an example, Williamson (1993) presents bounded rationality and opportunism as the principal behavioural assumptions on which transaction cost economics relies on. He acknowledges reputation embeddedness as a necessary trust enforcement mechanism, and because economic actors are victims of bounded rationality, organizational structures and centralized power are necessary. However, smart contracting and distributed trust presents us with a solution that might alter the traditional conception and understanding of transaction cost economics (Seidel, 2018).

Following a similar analogy, the theory of disruptive innovation is based on the traditional notion of organizational structures, explaining why many incumbent firms are facing problems under conditions of discontinuous change. However, Seidel (2018) argues that we currently do not have adequate organizational theory to describe and explain the economic activity that emerge from new distributed trust structures. While researchers slowly started to address shifting organizational boundaries after the technological shift to Web 2.0, the advent of distributed trust through blockchain technology also challenges the underlying trust assumptions, which might diminish the needs and benefits of formal organizations. Although the status of blockchain as a disruptive technology is debated (see Section 6.3.1), the implication for blockchain's ability to eliminate the role of intermediaries remains clear (e.g., Swan, 2016; Tapscott & Tapscott, 2016). Essentially, ledgers will no longer need a trusted third-party for validation, ranging from records of economic exchange and reputational systems, to certification of authenticity (Seidel, 2018).

When Airbnb employed new technology to disrupt the accommodation industry, they did not eliminate the existing intermediaries (i.e., hotels and bed & breakfasts). Instead, they competed for market shares by introducing radically new offerings. Hence, while Airbnb followed a traditional disruptive path, blockchain-based home-sharing startups do not essentially fit into the traditional model presented in disruptive theory. While disruptive theory emphasizes on the competition between incumbents and disruptive entrants, blockchain presents a constitutional change to the traditional logic. With a fundamental new trust structure, the incumbents are not *only* in danger of becoming outcompeted; much of their value proposition is simply being made redundant to the entire equation.

6.3.3 The Disruptive Potential of Blockchain Technology In Home-Sharing

As numerous scholars emphasize (e.g., Christensen & Raynor, 2003; Chesbrough, 2010; Markides, 2006), disruptive innovation is essentially a business model problem. Hence, by looking at the technological attributes of blockchain in a business model context, the *true* disruptive potential of blockchain-based home-sharing can be assessed. Consequently, based on the insights from preceding sections, we evaluate blockchain technology along the five key characteristics for disruptive innovations as presented in Section 3.1.3. The characteristics are presented prior to the corresponding discussion.

1. *The innovation is either a radical new technology breakthrough or a fundamentally new business model relative to existing offerings.*

As discussed in Section 6.3.2, blockchain technology proposes a significant innovation in the sharing economy, as it promises not only to replace incumbents, but essentially eliminate the key value proposition current intermediaries possess; namely the enablement of trustworthy exchanges. Due to its attributes of decentralization and the underlying cryptographic infrastructure, scholars argue that blockchain technology challenges any business model that relies on third parties for trust and verification (e.g., Beck & Müller-Block, 2017; Tapscott & Tapscott, 2016). Hence, it is undoubtedly a radical technological breakthrough that puts significant pressure on incumbents built on trusted-securing models.

Moreover, as Carlsson (1999) argues, when aiming to develop a disruptive business model, the most vital source of advantage is the new value chain's lower cost structure, as this enables the entrepreneurs to experiment with small investments. This characteristic is evident in Airbnb's disruptive trajectory in the short-term accommodation industry, as they own limited tangible assets compared to companies in the hospitality industry (Ward, 2018). Considering the decentralized governance of the new blockchain-based firms and the possibilities for automated enforcement, we are presented with a solution that can even more effectively connect supply and demand. Blockchain-based home-sharing startups only need a small team of coders and developers that can build and maintain the architecture of the platform. CryptoCribs, for instance (see Section 2.3.2), is mainly a two-man project that has managed to build an up-and-running platform that has attracted over 1500 hosts. Hence, despite marginal revenue from fees, this makes the business model highly lucrative for the creators if it gains traction. If the platform creates their own token for exchanges, such as Beenest (see Section 2.3.1), the value for the creators becomes even more evident, as the value of the tokens is directly linked to increased adoption of the platform

If blockchain based platforms gains traction, it proposes a massive threat to Airbnb. As Rampell (2015) puts it: "The battle between every startup and incumbent comes down to whether the startup gets distribution before the incumbent gets innovation." And to compete, Airbnb would rigorously have to "burn the boats (and everything and everyone else) to reduce overhead enough to compete on pricing (Ward, 2016)".

Much like the Internet, blockchain technology is best described as a foundational or general purpose technology (Iansiti & Lakhani, 2017; Kane, 2017; Trüschler, 2018). However, blockchain-based home-sharing platforms' categorization as true disruptive business models is debatable, and essentially remains to be seen ex post. One could argue that the attributes of blockchain technology (i.e., increased privacy protection, more secure payment systems, and enhanced safety) essentially are radical improvements in *current* business models, and does *not* represent a radical new way of doing business. However, the improvements does not equate to sustaining innovations either, making the assessment of disruptiveness challenging. While the business idea of home-sharing platforms mainly remains the same, it includes a radically different value proposition.

Matt, Hess and Benlian (2015) identify four essential dimensions of digital transformation of business models. These include: use of new technologies, changes in value creation, structural changes, and financial aspects. Consequently, as blockchain can bypass middlemen, and reduce transaction and agency costs (Boge & Nyrønning, 2017) by introducing concepts like trustless lending, smart contracts, tokens, ICOs, reputation protocols and consensus mechanisms (see Sections 2.1, 2.3 and 3.2), it does not follow the traditional sustaining trajectory of incremental innovations. Thus, blockchain-based home-sharing intrinsically presents a profoundly new business model compared to existing offerings, thus supporting its potential disruption.

2. *The innovation either starts by underperforming (low-end disruption) or overperforming (high-end disruption) mainstream attributes valued by the customers, or penetrate completely new markets (new-market disruption).*
3. *The attributes of the innovation is not initially valued by the mainstream customer market.*

Considering our results discussed in Section 6.1.3, the customer segments representing the best target group for blockchain-based home-sharing is the early adopters of Airbnb, preferably younger male students with a cryptocurrency interest. This represents a targeting strategy aimed at low-end niche markets, and thus appears to follow the trajectory of low-end disruption as proposed by Christensen (1997). Moreover, older females were the most demanding of improvements in relation to privacy, security and safety. However, it seems unlikely that blockchain-based home-sharing would be valued by these customers early on, as older people are generally more slow in adopting technology (e.g., Lee, & Coughlin, 2015).

Our results indicate that Airbnb have reached mainstream adoption, and we argue that price-sensitive, younger consumers propose attractive segments for blockchain-based acceptance. However, our findings show that consumer trust in the institution behind the sharing platform is rated higher than trust in strangers, which might limit the blockchain-based business model's initial mainstream attractiveness. Furthermore, the interest in cryptocurrencies is low amongst the respondents. Hence, in combination, our findings clearly suggest that blockchain-based home-sharing not initially will be valued by the mainstream consumers. This also relates well to findings from a survey conducted by Deloitte (2016), pointing to low awareness and understanding of the principal technology of blockchain in business environments, making it reasonable to assume that the awareness amongst consumers is even lower.

Moreover, as the technology is rather new, we argue that there is a need for further development regarding technical standards, safety, regulations and compliance in order to facilitate mass market adoption (Boge & Nyrønning, 2017). As Swan (2015) proposes, there are many issues that must be resolved before individuals feel comfortable storing their personal records in a decentralized manner. And as we previously have pointed out, the hacking of "The DAO" clearly illustrate the fatal effect of decentralization in the event of insufficient security frames. In such, it seems that blockchain-based home-sharing is best served by targeting niche markets of the identified early adopters of Airbnb, that might be the only enthusiastic segment that are able to envision its underlying potential and accept the associated risks (Moore, 2014).

4. *The innovation is either simpler, more convenient and cheaper (low-end disruption) or radical and more expensive (high-end disruption) than existing offerings.*

Blockchain technology enables cost-competitive pricing relative to current offerings by reducing intermediary service fees. However, the concept of blockchain-based home-sharing is not intrinsically a simple and more convenient service compared to e.g., Airbnb, as it provides a wide range of advanced technical attributes.

Christensen, Hall, Dillon, and Duncan (2016) argue that disruption theory primarily explains and predicts the behaviour of companies in danger of being disrupted, and does not tell entrepreneurs what products or services that can result in successful disrupting of a giant. To get *that* right, Christensen et al. (2016) argue that startups need to understand *the theory of jobs to be done*, stating that too many firms emphasize on improving their products without ever understanding *why* customers make the choices they do. With regards to home-sharing, this appears to be a critical factor of success, as customers do not buy services, but more precisely "hire" hosts and "platforms" to do a job (i.e., giving them a place to accommodate). Consequently, it is not just the value proposition in the form of property listings that is its primary function; it is just as important to create the right set of experiences for customers (Christensen et al., 2016).

The issue of trust for instance, is an emotional component that is difficult to quantify, but is a fundamental ingredient in any sharing transaction. And as our results also indicate, being cheaper and "good enough" will not guarantee commercial success; the foundation of successful innovation is to "know what job customers are hiring you to do before you can hope to create the perfect solution for them – one that they'll choose over all other options (Dillon, 2016)". And as indicated in Section 6.1.1 and 6.1.2, good experiences and trust increase use of home-sharing for existing users, while more sceptical non-consumers demand improvements in security, safety and privacy. Through enhancing the performance of the latter improvement areas, the platforms are perceived as more trustworthy. As Dillon (2016) concludes: "If you nail that, the rest will fall in line". And in such, the convenience of using blockchain-based home-sharing services could eventually also come about.

5. *Over time, sustaining innovations improve the disruptive offering's performance (low-end/new-market disruption) or affordability (high-end disruption) to a level where the innovation begins to attract the mainstream market.*

Airbnb has provided a solid backbone for the adoption of home-sharing services. In effect, it has also laid the basis for new startups to focus on identifying problems in existing offerings, and create solution for rectification. Without the trust shift partly materialized through the sharing economy and Airbnb making peer-to-peer accommodation a mainstream market service, the new series of blockchain-based platforms would have no foundation to build upon.

However, any discussion of the growth potential of new home-sharing platforms should acknowledge that many previous sharing platforms have struggled to gain traction (Manyika et al., 2016). While we can observe promising outlooks in increased adoption and awareness of blockchain applications (e.g., Statista, n.d.d predict that the global blockchain technology market has grown to 2.3 billion by 2021), any business with an ambition to enter the mainstream market must demonstrate how they can be of value to the early majority (Moore, 2014). Evans (2009, p. 21) state that "If the platform does not grow quickly enough to critical mass, early adopters lose interest, fewer later adopters come, and word-of-mouth referrals stop or turn negative". The early majority is characterized by customers who are pragmatic in nature, hence withholding any substantial investments until they see what others make of the new and innovative ideas (Moore, 2014).

We have identified that blockchain attributes can solve many of the identified improvement areas from users (i.e., privacy, safety and security). And as previously noted, Morgan Stanley (2017) recently found that safety and privacy issues are still the two dominant drivers of non-consumption of sharing services. Hence, blockchain-based home-sharing platforms have the potential to present solutions that exceeds the needs of early adopters. And as consumers become more comfortable with new technologies as adoption and awareness grow (Moore, 2014), this could also lead to new-market disruption (Christensen & Raynor, 2003).

To provide a final conclusion to the disruptive nature of blockchain technology in the home-sharing sector, we use the litmus tests (Christensen et al., 2002) introduced in Section 3.1.3. The results are presented in Table 22.

Table 22 Disruptive litmus test of blockchain-based home-sharing

Test	Disruption qualifiers	Does it qualify?	Comment
Low-End disruption:			
1	Are prevailing products more than good enough?	Partly	Airbnb have over 400 million listings worldwide, prices are increasing and the service has reached mainstream adoption. They also provide luxury listings, superhost status and social connections.
2	Can you create a different business model?	Yes	The technological attributes, new governance and cost structure, and decentralization enables entirely different business models.
New-Market disruption:			
1	Does the innovation target customers who in the past have not been able to "do it themselves" for lack of money or skills?	Partly	Blockchain-based home-sharing can eventually target segments currently sceptical of trusting new technology and sharing platforms
2	Is the innovation aimed at customers who will welcome a simple product?	No	
3	Will the innovation help customers do more easily and effectively what they are already trying to do?	Yes	By providing improvements that currently limit home-sharing usage

As shown in Table 22, despite our arguments of blockchain technology not intrinsically fitting the disruption theory framework, the disruptive potential of its utilization in home-sharing is visible. This becomes even more clear by evaluating the implementation of the technology into the Airbnb business model. While incumbents often are reluctant to implement disruptive innovations, and ends up in the innovator's dilemma (Christensen, 1997), Airbnb is well aware of the potential of blockchain technology, and already in early 2016 acquired a team of blockchain and cryptocurrency experts (Kar & Wong, 2016). Sometimes, incumbent firms manage to identify and exploit disruptive innovations before being disrupted by others (Christensen, 2006). Nevertheless, when they face challenges of trying to adapt to disruptive change, it is often a result of the capabilities that once made them successful (Christensen, 1997). An inevitable truth is that if Airbnb implements blockchain technology to the extent as proposed by CryptoCribs and Beenest, it will contradict their entire model for revenue generation. This enhances our argument that blockchain in home-sharing should not be seen as a sustaining innovation, and also further exemplifies the previous discussion of blockchain-based home-sharing not fitting the traditional disruptive framework (see Section 6.3.2). On one hand, incumbents like Airbnb cannot implement the technological innovation and become truly peer-to-peer blockchain-based home-sharing platforms without undermining their entire existential purpose. On the other hand, by doing nothing, Airbnb is likely to eventually be outcompeted by decentralized substitutes. Hence, Airbnb seems to be facing a dilemma much larger than the one conceptualized by Christensen's theory (1997), and instead appears to be on a trail of "destruct or get destructed".

However, blockchain technology is fairly new, existing blockchain-based home-sharing startups are either at development or early operational phase, and the blockchain "hype" have caused an explosive growth of crowdfunded decentralized applications. This indicates that entrepreneurs are rushing into the market (Orcutt, 2017; Trüschler, 2018). Moreover, while self-executing smart contracts governing sharing transaction in theory are open-source (i.e., can be reviewed by each individual capable of reading their specification), less tech-savvy users might have to trust the algorithm itself (Lustig & Nardi, 2015), and put faith in that it legally compliant (Al Khalil et al., 2017). This kind of blinded trust in technology would probably require regulations, and calls for a need of establishing a common language between developers and lawyers. While several states especially in the United States are moving quickly to codify smart contracts into their laws (Orcutt, 2018), this could be an early complicating factor for the successful development of blockchain-based home-sharing.

There will always be uncertainty whenever new radical technology is involved, and according to Swan (2015), the blockchain revolution is currently where the World Wide Web was at the last turn of the century; at the beginning of what is promised to be a long and spectacular journey (Swan, 2015). If the development of blockchain is reminiscent of the early Internet, broad acceptance will eventually follow. In a Harvard Business Review article from 1985, called "How Information Gives You Competitive Advantage", Michael Porter and Victor Millar predicted how the information technology (the Internet) would change the nature of competition, which could alter each of the five competitive forces, change industry structures, as well as be a source of competitive advantage for those leveraging it (Porter 1979; Porter & Miller, 1985). Despite obstacles and uncertainty, blockchain technology has the potential to reduce capitalism, reverse the laws of business structure, and truly empower the people in a peer-to-peer sharing economy. As concluded in Boge and Nyrønning (2017): blockchain technology will disrupt the current sharing economy landscape; the ultimate question is when. And as this tipping point occurs, and blockchain technology transforms from an enabling disruptive technology, to a *true* disruptive force, the potential for commercial success is enormous.

7 Conclusion and Implications for Further Research

In this thesis, we have investigated how blockchain technology have the capacity to fundamentally reshape the home-sharing segment by eliminating intermediaries. Using both descriptive statistics and exploratory structural equation modeling, we have mapped existing customer orientations, experiences and demands for improvements. Further, we have used the insights from our empirical analysis in combination with our literature review to assess the disruptive potential of blockchain-based home-sharing. This chapter presents the conclusion to our problem statement and provide implications for further research. We emphasize that our concluding remarks also serve as implications for entrepreneurs within blockchain-based home-sharing, who can use it as a tool to position their startup for success.

7.1 Conclusion

Our discussion has laid the basis for answering the following problem statement:

How can new blockchain-based home-sharing platforms succeed with disruptive innovation in the sharing economy?

First and foremost, entrepreneurs within the blockchain-based home-sharing sector should be pleased to see that the concept of home-sharing appears to have been accepted by the mass market. Furthermore, user adoption is still rising, indicating an existence of unsaturated markets. To outperform incumbents' value propositions and adjust to consumer needs, blockchain-based home-sharing startups should emphasize on providing security in payment systems, privacy protection of personal information and more solid insurance schemes. Concerning initial market entry, blockchain-based home-sharing startups are best served by targeting the low-end segment through competitive price offerings. In particular, they should direct their focus towards young, cost-sensitive males, with an interest for cryptocurrencies. Possible subsets can be found in students enrolled at technical universities, or young professional with an entrepreneurial mindset (e.g., located in startup hubs, crypto-communities, accelerators etc.). However, entrepreneurs should be aware that existing blockchain-based home-sharing platforms (CryptoCribs, BeeNest and Cryptobnb) are also targeting this group of users. Hence, there is an ongoing race of capturing these consumers. Furthermore, Europe proposes the most attractive target market, as home sharing is adopted at a more rapid pace than the other continents. Nevertheless, considering the high failure rate of blockchain-based startups, we recommend the new platforms to establish a solid business model, acquire an experienced team and formulate a long-term strategy before launching their platforms. It is especially important to ensure that the programming code is impeccable to avoid any security missteps (e.g., like The DAO) that could alter their integrity.

People tend to buy products or services if they are able to understand what it can do, and how it can bring them value. Blockchain technology and smart contract enforcement are relatively new and complex to the average consumer, and we find that interest in cryptocurrencies is currently low. Hence, this represents a barrier to mainstream adoption. In order to establish trust and foster understanding, we thus recommend that entrepreneurs develop marketing strategies that aims to enhance the understanding of the technology. This also involves exploiting the ongoing crypto-hype in society, and expose their new service offerings through media channels (e.g., online marketing of ICOs, blog-post, contributions on Reddit). To reach out to a wider audience in the advent of an ICO or platform launch, we recommend the startups to publish two whitepapers; one technically advanced for tech-savvy users, and one oriented towards the mainstream market, focused on the improvements in privacy, safety and security. Moreover, as cryptocurrencies and decentralized applications become more accepted among early adopters, it will serve as a catalizator on a path towards the mass market.

Although users still perceive review-systems to be the most important trust-building mechanism, several other information metrics give valuable insights. Hence, we recommend that the platform should be designed such that reviews from other sharing platforms and external references can be displayed in the host-profile (in addition to e.g., name, language, response time etc.). This will allow hosts to enhance their trustworthiness through increased transparency. Further, since third-party verification of IDs are important to users, entrepreneurs should look into how such verification is best implemented through the blockchain. Third party verifier must also be assessed, and considering that insights to social media accounts scores low on insight importance, more centralized governmental institutions might prove to be beneficial.

This outlined strategy appears to be the best road to success for blockchain-based home-sharing startups. And our results show that their disruptive potential against Airbnb with such an approach is notable, primarily due to their ability to decentralize, enforce and secure transactions at a marginal cost. However, it is key for these entrepreneurs to recognize that trust is the fundamental element of this disruption, being the most valuable currency for the success of decentralized transactions. Hence, exploring how to best design for trust is an inevitable necessity if the *trust machine* is going to be capable of disrupting the *trust business* of home-sharing platforms.

In spite of the positive outlooks, any entrepreneur entering the home-sharing market should look into domestic regulations that could be imposed on the short-term rental market in the respective country. Additionally, they should expect to face new legislations on self-enforcing smart contracts and privacy laws. Platforms should thus undergo regulatory compliance, and be designed in a way that makes them best suited to comply with future regulations.

Still, despite the uncertainties associated with regulations and technology complexity, blockchain-based home-sharing startups hold great promise and exciting times await. And as Alan Kay (1971) once said: “The best way to predict the future is to invent it (Andersen, 2013).”

7.2 Implications for Further Research

Despite the significant influence and benefits of blockchain technology in homesharing, a scarce amount of academic work has investigated the technology’s business applications within the sharing economy. Hopefully, our exploratory study into a rather new phenomenon will provide a solid basis for further exploration of this field. Yli-Huumo et al. (2016) argue that research on deployment of smart contracts is necessary to reveal and design better business models for digital transactions. Hence, in accordance with Yli-Huumo et al. (2016), and considering the rapid development of this technological field, we believe that high quality publications on this subject is needed. We especially welcome similar studies that explore the car-sharing sector, aiming to assess blockchain technology's disruptive potential against incumbents like Uber. Moreover, as our study is limited to data collected from Norwegian consumers who are relatively young, it would have been interesting to conduct other country-specific studies, examining consumers in dissimilar context and with a more dispersed age range.

Our thesis has explored consumer orientations and demands in order to evaluate blockchain's disruptive potential. However, considering the difficulties of using disruptive theory ex ante, we encourage other strategic management scholars to examine decentralized sharing economy startups through other theoretical lenses, such as *Diffusion Theory* or *Bounded Rationality Theory*. Hopefully, more focus within this field of research can bring valuable contributions in making a clearer distinction between the visionary hype and blockchain technology's true disruptive potential in the sharing economy.

As our study is limited with regards to its technical comprehension (i.e., the researchers does not have empirical background from computer science), we wish to advocate research that more precisely combines the technical attributes of blockchain with a strategic management approach. From such a collaborative angle, it would especially bring additional insight to conduct a thorough empirical study on the effects of blockchain technology on Transaction Cost Economics and Agency Costs within home-sharing. Furthermore, the shift from institutional to distributed trust presents a major barrier that needs to be overcome in order for blockchain-based platforms to succeed. Hence, we support Hawlitschek, et al. (2018), who calls for further research on how sharing platforms can be designed to facilitate distributed trust.

In relation to our market analysis of the home-sharing sector, our study is inconclusive in making precise implications regarding regulatory uncertainties. Moreover, as blockchain-based applications are more widely adopted, we expect additional regulations that might govern how the technology can be deployed. Hence, there are ample opportunities for making more concrete evaluations of how legal effects could influence blockchain-based home-sharing (and/or car-sharing).

Finally, in our study we have pointed out the difficulties of deploying the theoretical framework of disruption on blockchain-based innovations within the home-sharing segment. Thus, considering that blockchain technology represents a disruptive force of eliminating middlemen across all industries depending on third-party intermediaries, we encourage scholars to examine such applicability of disruption theory in more detail. Considering the recognition of the framework, such theoretical developments could hopefully bring increased attention towards research on blockchain-based applications.

Bibliography

Acemoglu, D., & Robinson, J. (2008). *The role of institutions in growth and development.* Washington DC: World Bank.

Adams, W. R. (2018). Strategic Implications of Blockchain. *Undergraduate Honor Thesis.* Brigham Young University.

Afthanorhan, W. M. A. B. W., Ahmad, S., & Mamat, I. (2014). Pooled Confirmatory Factor Analysis (PCFA) using structural equation modeling on volunteerism program: A step by step approach. *International Journal of Asian Social Science*, *4*(5), 642-653.

Ahmed, K. (2014). Carney puts bankers' pay in spotlight after misconduct shockwaves. Retrieved from: http://www.bbc.com/news/business-30079451

Airbnb (n.d.a). Fees for home bookings. Retrieved from: https://www.airbnb.ca/help/article/1857/what-is-the-airbnb-service-fee

Airbnb (n.d.b). How do I become a Superhost? Retrieved from: https://www.airbnb.com/help/article/829/how-do-i-become-a-superhost?locale=en

Airbnb (n.d.c). How do reviews work? Retrieved from: https://www.airbnb.com/help/article/13/how-do-reviews-work

Airbnb (n.d.d) How will my email address look to other people? Retrieved from: https://www.airbnb.com/help/article/694/how-will-my-email-address-look-to-other-people

Airbnb (n.d.e). San Francisco, CA. Retrieved from: https://www.airbnb.no/help/article/871/san-francisco--ca

Airbnb (n.d.f). New York, NY. Retrieved from: https://www.airbnb.no/help/article/868/new-york--ny

Airbnb (n.d.g.). What is the Airbnb host guarantee? Retrieved from: https://www.airbnb.no/help/article/279/what-is-the-airbnb-host-guarantee

Airbnb Newsroom (n.d.) Airbnb Fast Facts https://press.atairbnb.com/app/uploads/2017/08/4-Million-Listings-Announcement-1.pdf

Al Khalil, F., Butler, T., O'Brien, L., & Ceci, M. (2017). Trust in Smart Contracts is a Process, As Well. *International Conference on Financial Cryptography and Data Security*, 510-519.

Alavifar, A., Karimimalayer, M., & Anuar, M. K. (2012). Structural equation modeling vs multiple regression. *Engineering Science and Technology: An International Journal, 2*(2), 326-329.

Alexander, L. (2016) Why it's time to retire 'disruption', Silicon Valley's emptiest buzzword. Retrieved from: https://www.theguardian.com/technology/2016/jan/11/disruption-silicon-valleys-buzzword

Alford, H (2018) Why Blockchain Will Be An Engine For Inclusion. Retrieved from: https://medium.com/@harryalford3/why-blockchain-will-be-an-engine-for-inclusion-2842a8df333f

Allen, D., (1988). New Telecommunication Services: Network Externalities and Critical Mass. *Telecommunication Policy, 12*(3), 257–271.

Allen, D. (2017). Discovering and developing the blockchain crypto-economy.

Amit, R., & Zott, C. (2012). Creating value through business model innovation. *MIT Sloan Management Review*, *53*(3), 41.

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological bulletin, 103*(3), 411.

Andersen, E. (2013). Great Leaders Don't Predict the Future - They Invent It. Retrieved from: https://www.forbes.com/sites/erikaandersen/2013/07/10/great-leaders-dont-predict-the-future-they-invent-it/#7937614c6840

Andrews, F. M. (1984). Construct validity and error components of survey measures: A structural modeling approach. *Public opinion quarterly*, *48*(2), 409-442.

Anscombe, F. J. (1960). Rejection of outliers. *Technometrics*, *2*(2), 123-146.

Apodaca, R. (2017) A Gentle Introduction to Bitcoin Cold Storage. Retrieved from: https://bitzuma.com/posts/a-gentle-introduction-to-bitcoin-cold-storage/

Asparouhov, T., & Muthén, B. (2009). Exploratory structural equation modeling. *Structural equation modeling: a multidisciplinary journal*, *16*(3), 397-438.

Athey, S., Catalini, C., & Tucker, C. (2017). The digital privacy paradox: small money, small costs, small talk. *National Bureau of Economic Research*, w23488.

Atzori, M. (2015). Blockchain technology and decentralized governance: Is the state still necessary?

Audretsch, D. B. (2002). The dynamic role of small firms: Evidence from the US. In *Small firm dynamism in East Asia*, 13-40.

Babbie, E. (1989). *The Practice of Social Research* (5th Edition). Belmont, CA: Wadsworth

Bagozzi, R. P. (1991). Further thoughts on the validity of measures of elation, gladness, and joy. *Journal of Personality and Social Psychology*, *61*(1), 98.

Bagozzi, R. P., & Yi, Y. (2012). Specification, evaluation, and interpretation of structural equation models. *Journal of the academy of marketing science, 40*(1), 8-34.

Baldwin, C.Y., and Woodard, C.J. (2009). The Architecture of Platforms: A Unified View, in (Gawer, A., 'ed.' Platforms, Markets and Innovation (p. 9-34). Cheltenham, UK: Edward Elgar Publishing Limited, Bardhi, F., & Eckhardt, G. M. (2012). Access-based consumption: The case of car sharing. *Journal of consumer research*, *39*(4), 881-898.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of personality and social psychology, 51*(6), 1173.

Baum, J. A., Calabrese, T., & Silverman, B. S. (2000). Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. *Strategic management journal*, 267-294.

Beck, R., Czepluch, J. S., Lollike, N., & Malone, S. (2016). Blockchain-the Gateway to Trust-Free Cryptographic Transactions. *ECIS*, p. ResearchPaper153.

Becker, S., Bryman, A., & Ferguson, H. (Eds.) (2012). *Understanding research for social policy and social work: themes, methods and approaches*. UK: Policy Press.

Belk, R. (2009). Sharing. *Journal of consumer research*, *36*(5), 715-734.

Beenest (2018a). The Bee Token The Future of the Decentralized Sharing Economy. Retrieved from: https://s3-us-west-2.amazonaws.com/beenest-public/whitepaper/bee_whitepaper_v3.pdf

Beenest (2018b). What is Beenest? How The Bee Token is Revolutionizing The Home Sharing Market. Retrieved from: https://medium.com/@thebeetoken/what-is-beenest-how-the-bee-token-is-revolutionizing-the-home-sharing-market-8da32d79bbbb

Blair, R. C., & Higgins, J. J. (1980). The power of t and Wilcoxon statistics: A comparison. *Evaluation Review*, *4*(5), 645-656.

Bloomberg, J. (2017). Eight Reasons To Be Skeptical About Blockchain. Retrieved from: https://www.forbes.com/sites/jasonbloomberg/2017/05/31/eight-reasons-to-be-skeptical-about-blockchain/1.

Boge, V. M. B., & Nyrønning, M. Å. (2017). Disrupting the Disruptors? Introducing Sharing Economy 2.0 Utilizing Blockchain Technology and Decentralized Trust. *Project Thesis.* NTNU.

Bollen, K., & Lennox, R. (1991). Conventional wisdom on measurement: A structural equation perspective. *Psychological bulletin*, *110*(2), 305.

Bollier, D. (2015). How to Rein in Monopoly-like Network Platforms? Retrieved from: http://www.bollier.org/blog/how-rein-monopoly-network-platforms

Boomsma, A. (1985). Nonconvergence, improper solutions, and starting values in LISREL maximum likelihood estimation. *Psychometrika*, *50*(2), 229-242.

Botsman, R. (2012). The currency of the new economy is trust. Retrieved from: https://www.ted.com/talks/rachel_botsman_the_currency_of_the_new_economy_is_trust

Botsman, R. (2016). We've stopped trusting institutions and started trusting strangers. Retrieved from: https://www.ted.com/talks/rachel_botsman_we_ve_stopped_trusting_institutions_and_started_trusting_strangers

Botsman, R. (2017). *Who can you trust? How technology brought us together and why it might drive us apart.* NY: PublicAffairs

Botsman, R., & Rogers, R. (2010). *What's Mine Is Yours: The Rise of Collaborative Consumption.* NY: HarperBusiness.

Bower, J., & Christensen, C., (1995). Disruptive technologies: catching the wave. *Harvard Business Review,* 43-53.

Bray, I. (2017). Tru Reputation Protocol. Retrieved from: https://tru.ltd/Tru_Reputation_Protocol_White_Paper.pdf

Brown, T. A. (2014*). Confirmatory factor analysis for applied research*. NY: Guilford Publications.

Brown, T. A., & Moore, M. T. (2012). Confirmatory factor analysis. *Handbook of structural equation modeling*, 361-379.

Browne, M. W., & Cudeck, R. (1993). Alternative ways of assessing model fit. *Sage focus editions*, *154*, 136-136.

Bruno (2017) How to Read Bitcoin Blockchain Data on Blockexplorer? Retrieved from:https://bitfalls.com/2017/10/03/read-bitcoin-blockchain-data-blockexplorer/

Bryman, A. (2008). Social Research Methods (2nd Edition.). Oxford: Oxford University Press

Bryman, A. (2016). Social research methods. Oxford university press.

Bryman, A., & Bell, E. (2015). *Business research methods*. USA: Oxford University Press

Bryman, A. , Cramer, D. (2005). *Quantitative Data Analysis with SPSS12 and 13. A Guide for Social Scientists.* East Sussex: Routledge

Bryman, A., & Cramer, D. (2011). *Quantitative data analysis with IBM SPSS 17, 18 & 19—a guide for social scientists east sussex.* UK: Routdedge

Byrne, B. M. (2001). Structural equation modeling: Perspectives on the present and the future. *International Journal of Testing*, *1*(3-4), 327-334.

Bryne, B. M. (2010) *Structural Equation Modelling with AMOS: Basic Concepts, Applications and Programming* (2nd Edition). New York: Routledge, Taylor and Francis Group.

Buehler, K., Chiarella, D., Heidegger, H., Lemerle, M., Lal, A., & Moon, J. (2015). *Beyond the hype: Blockchains in capital markets* (No. 12). McKinsey Working Papers on Corporate & Investment Banking.

Burgen, S (2017) Barcelona cracks down on Airbnb rentals with illegal apartment squads. Retrieved from: https://www.theguardian.com/technology/2017/jun/02/airbnb-faces-crackdown-on-illegal-apartment-rentals-in-barcelona

Buterin, V. (2014). Ethereum White Paper. Retrieved from: https://github.com/ethereum/wiki/wiki/White-Paper

Cannon, S., & Summers, L. H. (2014). How Uber and the sharing economy can win over regulators. *Harvard business review*, *13*(10), 24-28.

Carlsson, B. (1999). Small business, entrepreneurship, and industrial dynamics. In *Are Small Firms Important? Their Role and Impact* (pp. 99-110). Boston, MA: Springer

Cartagena, J. (2014). 6 Challenges of the future of trust and reputation. Retrieved from: https://medium.com/ouishare-connecting-the-collaborative-economy/6-challenges-of-the-future-of-reputation-and-trust-4a1adedbfd72

Casey, M. (2016). The Blockchain: Decentralized trust to unlock a decentralized future. Retrieved from: https://www.oreilly.com/ideas/the-blockchain-decentralized-trust-to-unlock-a-decentralized-future

Catalini, C. (2017a). How Blockchain Applications Will Move Beyond Finance. *Harvard Business Review.*

Catalini, C. (2017b). How Blockchain Technology Will Impact the Digital Economy. *Oxford Business Law Blog.*

Catalini, C., & Gans, J. S. (2016). *Some simple economics of the blockchain*. *National Bureau of Economic Research,* w22952.

Chambers, J. M. (2017). *Graphical Methods for Data Analysis: 0*. London: Chapman and Hall/CRC.

Charitou, C. D. & Markides C. C. (2003). Responses to disruptive strategic innovation. *Sloan Management Review, 44*(2), 55-63

Chen, Y. (2017). Blockchain Tokens and the Potential Democratization of Entrepreneurship and Innovation. *Business Horizon*, forthcoming.

Chesbrough, H. (2010). Business model innovation: opportunities and barriers. *Long range planning*, *43*(2-3), 354-363.

Cheung, G. W., & Rensvold, R. B. (2002). Evaluating goodness-of-fit indexes for testing measurement invariance. *Structural equation modeling*, *9*(2), 233-255.

Chong, E. E., Nazim, A., & Ahmad, S. B. (2014). A comparison between individual confirmatory factor analysis and pooled confirmatory factor analysis: An analysis of library service quality, a case study at a public university in Terengganu. *International Journal of Engineering Science and Innovative Technology*, *3*(1), 110-116.

Chou, C. P., Bentler, P. M., & Satorra, A. (1991). Scaled test statistics and robust standard errors for non-normal data in covariance structure analysis: a Monte Carlo study. *British Journal of Mathematical and Statistical Psychology, 44*(2), 347-357.

Christensen, C. M. (1997). *The innovator's dilemma: when new technologies cause great firms to fail.* Boston, Mass.: Harvard Business School Press.

Christensen, C. M. (2001). Making friends with disruptive technology: -an interview with Clayton M. Christensen. *Strategy & Leadership*, *29*(2), 10-15.

Christensen, C. M. (2006). The ongoing process of building a theory of disruption. *Journal of Product innovation management*, *23*(1), 39-55.

Christensen, C. M., & Bower, J. L. (1996). Customer power, strategic investment, and the failure of leading firms. *Strategic management journal*, 197-218.

Christensen, C. M, Hall, T., Dillon, K. & Duncan, S. D. (2016). Know Your Customers' "Jobs to Be Done" Retrieved from:https://hbr.org/2016/09/know-your-customers-jobs-to-be-done

Christensen, C. M., Johnson, M. W., & Rigby, D. K. (2002). Foundations for growth: How to identify and build disruptive new businesses. *MIT Sloan Management Review*, *43*(3), 22.

Christensen, C. M., McDonald, R., Altman, E. J., & Palmer, J. (2016). *Disruptive innovation: intellectual history and future paths*. Harvard Business School.

Christensen, C. M., & Raynor, M. (2003). *The Innovator's Solution: Creating and Sustaining Successful Growth.* Boston, MA: Harvard Business School Press.

Christensen, C. M., Raynor, M. E., & McDonald, R. (2015). What is disruptive innovation. *Harvard Business Review*, *93*(12), 44-53.

Coase, R. (1937). The Nature of the Firm. *Economica, 4*(16), 386-405.

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2003). Outliers and multicollinearity: Diagnosing and solving regression problem II. *Applied multiple regression/correlation analysis for the behavioral sciences*, 390-430.

Coinmarketcap. (2018). Cryptocurrency Market Capitalizations. Retrieved from: https://coinmarketcap.com/all/views/all/

CoinSchedule (n.d.a). Cryptocurrency ICO Stats 2018. Retrieved from: https://www.coinschedule.com/stats.html?year=2018

CoinSchedule (n.d.b). Cryptocurrency ICO Stats 2017. Retrieved from: https://www.coinschedule.com/stats.html?year=2017

Cong, L. W., & He, Z. (2018). Blockchain disruption and smart contracts. *National Bureau of Economic Research*, w24399.

Conley, J. P. (2017). *Blockchain and the Economics of Crypto-tokens and Initial Coin Offerings* (No. 17-00008). Vanderbilt University Department of Economics.

Cook, R. D., & Weisberg, S. (1980). Characterizations of an empirical influence function for detecting influential cases in regression. *Technometrics*, *22*(4), 495-508.

Courtneidge, R. & Buelli, F. (2015) Blockchain and Financial Services - Industry snapshot and possible future developments. Retrieved from: https://www.innovalue.de/publikationen/InnovalueLockeLord-BlockchaininFinancialServices2015.pdf

Creswell, J. W., & Miller, D. L. (2000). Determining validity in qualitative inquiry. *Theory into practice*, *39*(3), 124-130.

Cronbach, L. J., & Meehl, P. E. (1955). Construct validity in psychological tests. *Psychological bulletin*, *52*(4), 281.

Crosby, M., Pattanayak, P., Verma, S., & Kalyanaraman, V. (2016). Blockchain technology: Beyond bitcoin. *Applied Innovation*, *2*, 6-10.

Cryptobnb. (2017). Whitepaper: A Blockchain-based marketplace and hospitality service for short-term rentals. Retrieved from: http://cryptobnbico.com/wp-content/uploads/2017/12/CryptoBnb-Whitepaper-v3.4.pdf

CryptoCribs. (2017). Whitepaper: A Peer-to-Peer Electronic Rental System. Retrieved from: https://www.cryptocribs.com/images/whitepaper.pdf

Danial, M. (2004). *Doing Quantitative Research in Education.* London: Sage

Danneels, E. (2004). Disruptive technology reconsidered: a critique and research agenda. *Journal of Product Innovation Management, 21*(4), 246-258.

Dapp, T. F., & Karollus, A. (2015). Blockchain–Angriff ist wahrscheinlich die beste Verteidigung. *Deutsche Bank Research. Aktueller Kommentar*.

Davidson, S., De Filippi, P., & Potts, J. (2016). Economics of blockchain. Fort Lauderdale, FL: Proceedings of Public Choice Conference.

De Filippi, P. (2015). What blockchain means for the sharing economy. *Harvard Business Review*.

Delahunty, T. (2018). Ethereum dApp CryptoCribs Outperforming ICO Projects. Retrieved from: https://www.newsbtc.com/2018/01/29/1850-cryptocribs-an-airbnb-for-crypto-enthusiasts/

Deloitte (2014) The Deloitte Consumer Review. Retrieved from: https://www2.deloitte.com/content/dam/Deloitte/uk/Documents/consumer-business/consumer-review-8-the-growing-power-of-consumers.pdf

Deloitte (2016). Deloitte survey: Blockchain reaches beyond financial services with some industries moving faster. Retrieved from: https://www2.deloitte.com/us/en/pages/about-deloitte/articles/press-releases/deloitte-survey-blockchain-reaches-beyond-financial-services-with-some-industries-moving-faster.html

Delphi (2017). The Oracle Problem. Retrieved from: https://medium.com/@DelphiSystems/the-oracle-problem-856ccbdbd14f

Dennis, R., & Owen, G. (2015). Rep on the block: A next generation reputation system based on the blockchain. *Internet Technology and Secured Transactions,* 31-138.

Dhillon, V., Metcalf, D., & Hooper, M. (2017). *Blockchain Enabled Applications: Understand the Blockchain Ecosystem and How to Make it Work for You*. NY: Apress.

Díaz, J., & Torras, C. (2012). A personal account of Turing's imprint on the development of computer science. *Computer Science Review, 6*, 225-234.

Dillon, K. (2016). What Airbnb Understands About Customers' "Jobs to Be Done". Retrieved from: https://hbr.org/2016/08/what-airbnb-understands-about-customers-jobs-to-be-done

Doering, D. S. & Parayre, R. (2000). *Identification and Assessment of Emerging Technologies.* In: Wharton on Managing Emerging Technologies. G.S. Day, P.J.H. Schoemaker, and R.E. Gunther (eds.). New York: Wiley.

Dourado, E., & Brito, J. (2014). Cryptocurrency. The New Palgrave Dictionary of Economics. *Online Edition. http://doi. org/10.1057/10.1057/9780230226203.3924*.

Dudovskiy, J. (2016). *The Ultimate Guide to Writing a Dissertation in Business Studies: A Step-by-Step Assistance.* Pittsburgh, USA.

DuPont, Q. (2017). *Experiments in algorithmic governance: A history and ethnography of "The DAO," a failed decentralized autonomous organization.* In Campbell-Verduyn, M. (Ed.) *Bitcoin and Beyond: Cryptocurrencies, Blockchains and Global Governance.* Abingdon: Routledge.

Earle, T. C. (2009). Trust, confidence, and the 2008 global financial crisis. *Risk Analysis*, *29*(6), 785-792.

Edelsbrunner, P. & Thurn, C (n.d.) Structural Equation Modeling. Retrieved from: http://blog.efpsa.org/2015/12/14/structural-equation-modeling-what-is-it-what-does-it-have-in-common-with-hippie-music-and-why-does-it-eat-cake-to-get-rid-of-measurement-error/

Eikemo, T. A., & Clausen, T. H. (Eds.). (2012). *Kvantitativ analyse med SPSS: en praktisk innføring i kvantitative analyseteknikker*. Trondheim: Tapir akademisk forlag.

Einav, L., Farronato, C., & Levin, J. (2016). Peer-to-peer markets. *Annual Review of Economics*, *8*, 615-635.

Eisenmann, T., Parker, G., & Van Alstyne, M. W. (2006). Strategies for two-sided markets. Harvard business review, 84(10), 92.

Eisenegger M. (2009). Trust and reputation in the age of globalisation. *Reputation Capital,* 11–22.

Eisenhardt, K. M. (1989). Agency theory: An assessment and review. *Academy of management review, 14(1)*, 57-74.

Elsevier .(n.d.). Journal Metrics. Retrieved from: https://journalmetrics.scopus.com/

eMarketer (2018). eMarketer Lowers Airbnb Forecast. Retrieved from: https://www.emarketer.com/content/emarketer-lowers-airbnb-forecast

Ert, E., Fleischer, A., & Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism Management*, *55*, 62-73.

Evans, D. S. (2009). How catalysts ignite: the economics of platform-based start-ups. *Platforms, markets and innovation*, 99-128.

Evans, P., Aré, L., Forth, P., Harlé, N., & Portincaso, M. (2016). Thinking Outside the Blocks. A Strategic Perspective on Blockchain and Digital Tokens. Retrieved from: https://www.bcg.com/blockchain/thinking-outside-the-blocks.html

Fan, X., Thompson, B., & Wang, L. (1999). Effects of sample size, estimation methods, and model specification on structural equation modeling fit indexes. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 56-83.

Fan, X., & Wang, L. (1998). Effects of potential confounding factors on fit indices and parameter estimates for true and misspecified SEM models. *Educational and Psychological Measurement, 58(*5), 701-735.

Fanning, K., & Centers, D. P. (2016). Blockchain and its coming impact on financial services. *Journal of Corporate Accounting & Finance*, *27*(5), 53-57.

Farr, C. (2017). Uber drivers in Norway fear losing their license, or even their car. Retrieved from: https://www.cnbc.com/2017/05/02/uber-drivers-in-norway-fear-losing-license-or-car.html

Fiedler, M. & Sandner, P. (2017)Identifying Leading Blockchain Startups on a Worldwide Level. Retrieved from: https://medium.com/@philippsandner/analysis-of-leading-blockchain-startups-worldwide-8ecee1a7d670

Field, A. (2005). Exploratory factor analysis. Discovering statistics using SPSS, 619-680.

Field, A. (2009). *Discovering statistics using SPSS*. London: Sage Publications.

Finch, J. F., West, S. G., & MacKinnon, D. P. (1997). Effects of sample size and nonnormality on the estimation of mediated effects in latent variable models. S*tructural Equation Modeling: A Multidisciplinary Journal, 4*(2), 87-107.

Flament, C. A. Blockchain technology: A general purpose technology for the decentralization of governance?.

Flieswasser, K. (2017). Will blockchain disrupt or go bust? Retrieved from: https://www.topbots.com/6-challenges-preventing-widespread-blockchain-technology-adoption/.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of marketing research*, 382-388.

Foster, R., & Kaplan, S. (2011). *Creative Destruction: Why companies that are built to last underperform the market--And how to successfully transform them*. NY: Crown Business.

Fradkin, A. (2017). Search, matching, and the role of digital marketplace design in enabling trade: Evidence from airbnb.

Franco, P. (2015). *Understanding bitcoin: Cryptography, engineering and economics*. New York, NY: Wiley.

Freeman, J., Carroll, G. R., & Hannan, M. T. (1983). The liability of newness: Age dependence in organizational death rates. *American Sociological Review*, *48*, 692-710.

Friedlmaier, M., Tumasjan, A., & Welpe, I. M. (2017). Disrupting industries with blockchain: The industry, venture capital funding, and regional distribution of blockchain ventures.

Friedman, D. D. (2008). *Future imperfect: technology and freedom in an uncertain world.* NY: Cambridge University Press.

Friedman, E., Kuwabara, K., Resnick, P., & Zeckhauser, R. (2000). Reputation systems: Facilitating trust in internet interactions. *Communications of the ACM, 43*(12), 45 –48.

Gallup (2017a) Trust in Institutions. Retrieved from: http://news.gallup.com/poll/1597/confidence-institutions.aspx

Gambardella, A., & McGahan, A. M. (2010). Business-model innovation: General purpose technologies and their implications for industry structure. *Long range planning*, *43*(2-3), 262-271.

Gambetta, D. (2000). Can we trust trust. *Trust: Making and breaking cooperative relations*, *13*, 213-237.

Gans, J. (2015) Why Apple and its iPhone confound disruption theorists. Retrieved from: https://theconversation.com/why-apple-and-its-iphone-confound-disruption-theorists-38205

Gansky, L. (2010). *The mesh: Why the future of business is sharing*. London: Penguin.

Gao, S., Mokhtarian, P., & Johnston, R. (2008). Nonnormality of data in structural equation models. *Journal of the Transportation Research Board*, (2082), 116-124.

Gay, L. R., Mills, G. E., & Airasian, P. W. (2009). *Educational research: Competencies for analysis and application*s (9th Edition). New Jersey: Prentice Hall

Gebbia, J. (2016). How Airbnb designs for trust. Retrieved from: https://www.ted.com/talks/joe_gebbia_how_airbnb_designs_for_trust/transcript

Gefen, D. (2000). E-commerce: the role of familiarity and trust. *Omega*, *28*(6), 725-737.

Gerbing, D. W., & Anderson, J. C. (1984). On the meaning of within-factor correlated measurement errors. *Journal of Consumer Research*, *11*(1), 572-580.

Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., & Goodwill, A. (2018). Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings. *Journal of Travel & Tourism Marketing*, *35*(1), 46-56.

Gilbert, C. (2003). The disruption opportunity. *MIT Sloan Management Review*, *44*(4), 27.

Golafshani, N. (2003). Understanding reliability and validity in qualitative research. *The qualitative report*, *8*(4), 597-606.

Goodwin, T. (2015). The battle is for the customer interface. Retrieved from: https://techcrunch.com/2015/03/03/in-the-age-of-disintermediation-the-battle-is-all-for-the-customer-interface/?guccounter=1

Gosling, S. D., Rentfrow, P. J., & Swann Jr, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in personality*, *37*(6), 504-528.

Govindarajan, V., & Kopalle, P. K. (2006). The usefulness of measuring disruptiveness of innovations ex post in making ex ante predictions. *Journal of Product Innovation Management, 23*(1), 12-18.

Greenberg, A. (2014). Nakamoto's Neighbor: My Hunt For Bitcoin's Creator Led To A Paralyzed Crypto Genius. Retrieved from: https://www.forbes.com/sites/andygreenberg/2014/03/25/satoshi-nakamotos-neighbor-the-bitcoin-ghostwriter-who-wasnt/#791967ad4a37

Guba, E. G. (1981). Criteria for assessing the trustworthiness of naturalistic inquiries. *Educational Resources Information Center Annual Review Paper, 29*(2), 75-91

Gurran, N., & Phibbs, P. (2017). When tourists move in: how should urban planners respond to Airbnb?. *Journal of the American planning association*, *83*(1), 80-92.

Guttentag, D. (2015). Airbnb: disruptive innovation and the rise of an informal tourism accommodation sector. *Current issues in Tourism*, *18*(12), 1192-1217.

Gutiérrez, J., García-Palomares, J. C., Romanillos, G., & Salas-Olmedo, M. H. (2017). The eruption of Airbnb in tourist cities: Comparing spatial patterns of hotels and peer-to-peer accommodation in Barcelona. *Tourism Management*, *62*, 278-291.

Hair, J. F., Anderson, R. E., Tatham, R. L., & William, C. (1995). *Multivariate data analysis with readings.* New Jersey: Prentice Hall.

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (1998). Multivariate data analysis. *Prentice Hall, 5*(3), 207-219.

Hair, J.F., Black, W.C., Babin, B. J., & Anderson, R.E. (2014). *Multivariate Data Analysis* (7th Edition). London: Pearson Education Limited.

Hair, J. F., Ringle, C. M., & Sarstedt, M. (2011). PLS-SEM: Indeed a silver bullet. *Journal of Marketing theory and Practice*, *19*(2), 139-152.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the academy of marketing science*, *40*(3), 414-433.

Hamari, J., Sjöklint, M., & Ukkonen, A. (2016). The sharing economy: Why people participate in collaborative consumption. *Journal of the Association for Information Science and Technology*, *67*(9), 2047-2059.

Harrell, F. E., Lee, K. L., & Mark, D. B. (1996). Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. Statistics in medicine, 15(4), 361-387.

Hawlitschek, F., Notheisen, B., & Teubner, T. (2018). The limits of trust-free systems: A literature review on blockchain technology and trust in the sharing economy. *Electronic Commerce Research and Applications*, *29*, 50-63.

Henderson, R. (2006). The innovator's dilemma as a problem of organizational competence. *Journal of Product Innovation Management*, *23*(1), 5-11.

Henderson, R., & Clark, K. B. (1990). Architectural innovation: the reconfiguration of existing product technologies and the failure of established firms. *Administrative science quarterly, 1*, 9-30.

Hileman, G. (2015, January). The bitcoin market potential index. *Springer*, 92-93.

Hitt, M. A., Ireland, R. D., Camp, S. M., & Sexton, D. L. (2001). Strategic entrepreneurship: Entrepreneurial strategies for wealth creation. *Strategic management journal*, *22*(6-7), 479-491.

Hira, A., & Reilly, K. (2017). The emergence of the sharing economy: Implications for development. *Journal of Developing Societies*, *33*(2), 175-190.

Hollensen, S. (2008). *Essentials of global marketing*. Essex, UK: Pearson Education.

Holmes-Smith, P., Coote, L., & Cunningham, E. (2006). Structural equation modeling: From the fundamentals to advanced topics. *Melbourne: SREAMS*.

Holton, E. F. III, & Burnett, M. F. (1997). Quantitative research methods In: Swanson, R. A. and Holton, E. F. III (Eds.) *Human resource development research handbook: Linking research and practice*, 65-87.

Hong, I. B., & Cho, H. (2011). The impact of consumer trust on attitudinal loyalty and purchase intentions in B2C e-marketplaces: Intermediary trust vs. seller trust. *International Journal of Information Management*, *31*(5), 469-479.

Hooper, D., Coughlan, J., & Mullen, M. (2008). Structural equation modelling: Guidelines for determining model fit. *Articles*, 2.

Horton, J., & Golden, J. (2015). Reputation inflation: Evidence from an online labor market. Work. Pap., NYU.

Hosmer, L. T. (1995) Trust: The Connecting Link Between Organizational Theory and Philosophical Ethics. *Academy of Management Review, 20,* 379-403.

Hsieh, Y. C., & Hiang, S. T. (2004). A study of the impacts of service quality on relationship quality in search-experience-credence services. *Total Quality Management & Business Excellence*, *15*(1), 43-58.

Hu, L. T., & Bentler, P. M. (1998). Fit indices in covariance structure modeling: Sensitivity to underparameterized model misspecification. *Psychological methods*, *3*(4), 424.

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal*, *6*(1), 1-55.

Hu, L. T., Bentler, P. M., & Kano, Y. (1992). Can test statistics in covariance structure analysis be trusted?. *Psychological bulletin, 112*(2), 351.

Hulland, J. (1999). Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic management journal*, 195-204.

Iansiti, M., and K. R. Lakhani (2017). The Truth About Blockchain. *Harvard Business Review, 95*(1), 118–127.

InsideAirbnb (n.d.). About Inside Airbnb. Retrieved from: http://insideairbnb.com/about.html

Ito, J., N. Narula, and R. Ali (2017). The Blockchain Will Do to the Financial System What the Internet Did to Media. *Harvard Business Review.*

Jacobs, J., A. (2018). Blockchain Oracles, Explained Retrieved from: https://scooblr.com/blockchain-oracles-explained/

Jahanmir, S. F., & Lages, L. F. (2016). The late-adopter scale: A measure of late adopters of technological innovations. *Journal of Business Research*, *69*(5), 1701-1706.

Jarvenpaa, S.L., Tractinsky, N., and Saarinen, L. (1999). Consumer trust in an internet store: a cross culture validation. *Journal of Computer Mediated Communication, 5*, 1–35.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of financial economics, 3*(4), 305-360.

John, N. A. (2013). The social logics of sharing. *The Communication Review, 16*(3), 113-131.

John, O. P., & Srivastava, S. (1999). The Big Five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of personality: Theory and research*, *2*(1999), 102-138.

Johnson, R. B., & Christensen, L. B. (2004). *Educational research: Quantitative, qualitative, and mixed approaches.* Boston, MA: Allyn and Bacon.

Johnson, D. R., & Creech, J. C. (1983). Ordinal measures in multiple indicator models: A simulation study of categorization error. *American Sociological Review, 48*, 398-407.

Johnston, D., Yilmaz, S. O., Kandah, J., Bentenitis, N., Hashemi, F., Gross, R., ... & Mason, S. (2014). The general theory of decentralized applications, dapps. GitHub.

Jorgenson, E. (2015). The power of network effects. Why they make such valuable companies, and how to harness them. Retrieved from: https://medium.com/evergreen-business-weekly/the-power-of-network-effects-why-they-make-such-valuable-companies-and-how-to-harness-them-5d3fbc3659f8

Jöreskog, K. G. (1969). A general approach to confirmatory maximum likelihood factor analysis. *Psychometrika*, *34*(2), 183-202.

Kakar, V., Franco, J., Voelz, J., & Wu, J. (2016). Effects of host race information on Airbnb listing prices in San Francisco.

Kane, G. C. (2016). Crowd-Based Capitalism? Empowering Entrepreneurs in the Sharing Economy. *MIT Sloan Management Review, 57*(3). 127-133.

Kane, E. (2017). Is Blockchain a General Purpose Technology?. RMIT University, Faculty of Business

Kang, H. (2013). The prevention and handling of the missing data. *Korean journal of anesthesiology*, *64*(5), 402-406.

Kamal, P., & Chen, J. Q. (2016). Trust in Sharing Economy. *PACIS*, 109.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business horizons*, *53*(1), 59-68.

Kar, I. J. & Wong, I. (2016) Airbnb just acquired a team of bitcoin and blockchain experts. Retrieved from. https://qz.com/657246/airbnb-just-acquired-a-team-of-bitcoin-and-blockchain-experts/

Kasireddy, P. (2017). Bitcoin, Ethereum, Tokens, ICOs. Why should anyone care? Retrieved from: https://hackernoon.com/bitcoin-ethereum-blockchain-tokens-icos-why-should-anyone-care-890b868cec06

Kenny, D. A. (2014). Measuring model fit. Retrieved from: http://davidakenny.net/cm/fit.htm

Kettley, S. (2017) CryptoBNB: An AirBnB alternative promising a smarter blockchain for better travel. Retrieved from: https://www.express.co.uk/finance/city/886434/cryptobnb-airbnb-alternative-blockchain-cryptocurrency-token-rental-travel

Khatwani, S. (2018) Bitcoin Private Keys: Everything You Need To Know. Retrieved from: https://coinsutra.com/bitcoin-private-key/

Killick, R. (2015). Sharing economy' companies like Uber and Airbnb aren't really 'sharing' anything. Retrieved from: http://www.businessinsider.com/sharing-economy-companies-like-uber-andairbnb-arent-really-sharing-anything-2015-10?r=US&IR=T&IR=T

Kim, J. O., & Curry, J. (1977). The treatment of missing data in multivariate analysis. *Sociological Methods & Research*, *6*(2), 215-240.

King, A. A., & Baatartogtokh, B. (2015). How useful is the theory of disruptive innovation? *MIT Sloan Management Review*, *57*(1), 77.

Kinnear, P. R., & Gray, C. D. (2009). *PASW Statistics 17 Made Simple: Replaces SPSS Statistics 17*. Psychology Press.

Kiviat, T. I. (2015). Beyond bitcoin: Issues in regulating blockchain transactions. *Duke LJ*, *65*, 569.

Kline, R.B. (2005). *Principles and Practice of Structural Equation Modeling* (2nd Edition). New York: The Guilford Press.

Kline, R. B. (2011). *Principles and Practice of Structural Equation Modeling* (3rd Edition). NY: Guilford Press.

Korosec, K (2018) This Is the Personal Data that Facebook Collects—And Sometimes Sells. Retrieved from: http://fortune.com/2018/03/21/facebook-personal-data-cambridge-analytica/

Kosba, A., Miller, A., Shi, E., Wen, Z., & Papamanthou, C. (2016). Hawk: The blockchain model of cryptography and privacy-preserving smart contracts. *Security and Privacy (SP),* 839-858.

Kothari, C. R. (2004). Research methodology: Methods and techniques. *New Age International*.

Krabel, S., & Mueller, P. (2009). What drives scientists to start their own company? An empirical investigation of Max Planck Society scientists. *Research Policy*, *38*(6), 947-956.

Larsen, W. A., & McCleary, S. J. (1972). The use of partial residual plots in regression analysis. *Technometrics, 14*(3), 781-790.

Lee, J. (1994). Odds ratio or relative risk for cross-sectional data?. *International Journal of Epidemiology*, *23*(1), 201-203.

Lee, C., & Coughlin, J. F. (2015). PERSPECTIVE: Older adults' adoption of technology: an integrated approach to identifying determinants and barriers. *Journal of Product Innovation Management*, *32*(5), 747-759.

Lei, P. W., & Wu, Q. (2007). Introduction to structural equation modeling: Issues and practical considerations. *Educational Measurement: issues and practice, 26*(3), 33-43.

Leidecker, J. K., & Bruno, A. V. (1984). Identifying and Using Critical Success Factors. *Long Range Planning*, *17* (1), 23-32.

Lemieux, V. L. (2016). Trusting records: is Blockchain technology the answer? *Records Management Journal*, *26*(2), 110-139.

Lepore, J. (2014). The disruption machine. *The New Yorker*, *23*, 30-6.

Leonard-Barton, D. (1992). Core capabilities and core rigidities: A paradox in managing new product development. *Strategic management journal*, *13*(S1), 111-125.

Lewicki, R. J., & Bunker, B. B. (1995). Trust in relationships. *Administrative Science Quarterly*, *5*(1), 583-601.

Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology*, *49*(4), 764-766.

Li, S., Glass, R., & Records, H. (2008). The influence of gender on new technology adoption and use–mobile commerce. *Journal of Internet Commerce*, *7*(2), 270-289.

Lieber, R. (2015). Airbnb horror story points to need for precautions. Retrieved from http://www.nytimes.com/2015/08/15/yourmoney/airbnb-horror-story-points-to-need-for-precautions.html.

Lincoln, Y. S. & Guba, E. G. (1985). *Naturalistic inquiry*. Beverly Hills, CA: Sage.

Lindgardt, Z., Reeves, M., Stalk Jr, G., & Deimler, M. (2009). Business model innovation: When the game gets tough, change the game. *Own the future: 50 ways to win from The Boston Consulting Group*, 291-298.

Little, R. J. (1992). Regression with missing X's: a review. *Journal of the American Statistical Association*, *87*(420), 1227-1237.

Lovins, L. H., & Cohen, B. (2011). *Climate capitalism: Capitalism in the age of climate change*. Hill and Wang.

Luhmann, N. (2018). *Trust and power*. US, New Jersey: John Wiley & Sons.

Lundy, L. (2016), Blockchain and the sharing economy 2.0. Retrieved from: https://www.ibm.com/developerworks/library/iot-blockchain-sharing-economy/index.html

Lustig, C., & Nardi, B., (2015). Algorithmic authority: The case of Bitcoin. *HICSS,* 743–752. doi:10.1109/HICSS.2015.95

Ma, X., Hancock, J. T., Mingjie, K. L., & Naaman, M. (2017). Self-Disclosure and Perceived Trustworthiness of Airbnb Host Profiles.*CSCW*, 2397-2409.

MacDonald, T. J., Allen D. W. E., & Potts, J. (2016). Blockchains and the Boundaries of Self-Organized Economies: Predictions for the Future of Banking. In Tasca, P., Aste, T., Pelizzon, L., & Perony, N. (Eds.), Banking Beyond Banks and Money. New Economic Windows (279-296). Springer.

Maharajh, R. (2016). The Future Has Arrived. Retrieved from: https://medium.com/not-evenly-distributed/the-future-has-arrived-fed56cec3266

Maine, E., & Garnsey, E. (2006). Commercializing generic technology: The case of advanced materials ventures. *Research Policy*, *35*(3), 375-393.

Mainelli, M., & Smith, M. (2015). Sharing ledgers for sharing economies: an exploration of mutual distributed ledgers (aka blockchain technology). *The Journal of Financial Perspectives*, *3*(3 Winter), 38–69.

Manyika, J., Lund, S., Bughin, J., Robinson, K., Mischke, J., & Mahajan, D. (2016). Independent work: Choice, necessity, and the gig economy. *McKinsey & Company. October*.

Manuel, S. & Andrews, S. (2016). Blockchain technology: Is 2016 the year of the blockchain? Retrieved from:
https://blogs.thomsonreuters.com/answerson/blockchain-technology/

Manzini, R., Lazzarotti, V., & Pellegrini, L. (2017). How to remain as closed as possible in the open innovation era: the case of Lindt & Sprüngli. *Long range planning*, *50*(2), 260-281.

Makridakis, S., Polemitis, A., Giaglis, G., & Louca, S. (2018). Blockchain: Current Achievements, Future Prospects/Challenges and its Combination with AI.

Markides, C. (2006). Disruptive innovation: in need of better theory. *Journal of Product Innovation Management, 23*(1), 19-25.

Marsh, H. W. (1998). Pairwise deletion for missing data in structural equation models: Nonpositive definite matrices, parameter estimates, goodness of fit, and adjusted sample sizes. *Structural Equation Modeling: A Multidisciplinary Journal*, *5*(1), 22-36.

Marsh, H. W., Morin, A. J., Parker, P. D., & Kaur, G. (2014). Exploratory structural equation modeling: An integration of the best features of exploratory and confirmatory factor analysis. *Annual review of clinical psychology*, *10*, 85-110.

Martin, P., Bateson, P. P. G., & Bateson, P. (1993). *Measuring behaviour: an introductory guide*. Cambridge UK: Cambridge University Press.

Martyn, P. (2018). Does Blockchain Provide The New Standard For Transparency? Retrieved from: https://www.forbes.com/sites/paulmartyn/2018/03/28/does-blockchain-provide-the-new-standard-for-transparency/2/#1f4fe8a32114

Massa, L., & Tucci, C. L. (2013). Business model innovation. *The Oxford Handbook of Innovation Management, Oxford University Press, Oxford*, 420-441.

Matt, C., Hess, T., & Benlian, A. (2015). Digital transformation strategies. *Business & Information Systems Engineering*, *57*(5), 339-343.

Mattila, J. (2016). *The Blockchain Phenomenon–The Disruptive Potential of Distributed Consensus Architectures* (No. 38). The Research Institute of the Finnish Economy.

Mauri, R. (2017). Three features of blockchain that help prevent fraud. Retrieved from: https://www.ibm.com/blogs/blockchain/2017/09/three-features-of-blockchain-that-help-prevent-fraud/

Mazzocchi, M. (2008). *Statistics for marketing and consumer research*. US, CA: Sage.

McCrae, R. R., & Costa Jr, P. T. (1999). A five-factor theory of personality. *Handbook of personality: Theory and research*, *2*, 139-153.

McLean, J. (2016) Banking on Blockchain: Charting the Progress of Distributed Ledger Technology in Financial Services. Retrieved from: https://www.ingwb.com/media/1609652/banking-on-blockchain.pdf

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological methods*, *17*(3), 437.

Medici (2017). 21 Companies Leveraging Blockchain for Identity Management and Authentication. Retrieved from: https://medium.com/@gomedici/21-companies-leveraging-blockchain-for-identity-management-and-authentication-d09d88e3a4bf

Micceri, T. (1989). The unicorn, the normal curve, and other improbable creatures. *Psychological bulletin, 105*(1), 156.

Mitchell, D., & Coles, C. (2003). The ultimate competitive advantage of continuing business model innovation. *Journal of Business Strategy*, *24*(5), 15-21.

Mittendorf, C. (2017). The Implications of Trust in the Sharing Economy–An Empirical Analysis of Uber. In *Proceedings of the 50th Hawaii International Conference on System Sciences*.

Molla, R. (2017) *Airbnb is on track to rack up more than 100 million stays this year — and that's only the beginning of its threat to the hotel industry.* Retrieved from: https://www.recode.net/2017/7/19/15949782/airbnb-100-million-stays-2017-threat-business-hotel-industry

Moody's Global Credit Research (2016). *Credit Strategy Blockchain Technology: Robust, Cost-effective Applications Key to Unlocking Blockchain's Potential Credit Benefits*. Retrieved from: http://www.alacrastore.com/moodys-credit-research/Credit-Strategy-Blockchain-Technology-Robust-Cost-effective-Applications-Key-to-Unlocking-Blockchain-s-Potential-Credit-Benefits-PBC_1023913

Moore, G. A. (2014*). Crossing the chasm* (3rd Edition). New York, NY: HarperCollins Publishers.

Morgan Stanley (2017). Surprising Airbnb Adoption Slowdown in US/EU, and What It Means for Hotels and OTAs. Retrieved from: http://www.fullertreacymoney.com/system/data/files/PDFs/2017/November/16th/ARCOST20171023211633_73976052-b837-11e7-863e-cb02ae2926cb_DigitalPremium.pdf

Moss, S., Prosser, H., Costello, H., Simpson, N., Patel, P., Rowe, S., ... & Hatton, C. (1998). Reliability and validity of the PAS-ADD Checklist for detecting psychiatric disorders in adults with intellectual disability. *Journal of Intellectual Disability Research*, *42*(2), 173-183.

Munoz, P., & Cohen, B. (2017). Mapping out the sharing economy: A configurational approach to sharing business modeling. *Technological Forecasting and Social Change*, *125*, 21-37.

Myler, L. (2017). Transparent Transactions: How Blockchain Payments Can Make Life Easier For B2B Companies. Retrieved from: https://www.forbes.com/sites/larrymyler/2017/11/09/transparent-transactions-how-blockchain-payments-can-make-life-easier-for-b2b-companies/#685e481070b5

Möhlmann, M. (2015). Collaborative consumption: determinants of satisfaction and the likelihood of using a sharing economy option again. *Journal of Consumer Behaviour*, *14*(3), 193-207.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Retrieved from: https://bitcoin.org/bitcoin.pdf

Newman, R. & Antin, J. (2016). Building for Trust. Retrieved from: https://medium.com/airbnb-engineering/building-for-trust-503e9872bbbb

Newman, R., Chang, V., Walters, R. J., & Wills, G. B. (2016). Web 2.0—The past and the future. *International Journal of Information Management*, *36*(4), 591-598.

Norton, J. (2016). *Blockchain Easiest Ultimate Guide To Understand Blockchain.* CreateSpace Independent Publishing Platform

Noyes, C. (2016). Bitav: Fast anti-malware by distributed blockchain consensus and feedforward scanning. *arXiv preprint arXiv:1601.01405*.

Nunnaly, J. (1978). *Psychometric theory*. New York: McGraw-Hill.

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd Edition). New York: McGrawHill.

Nwonu, E. (2017). The next innovation wave: Startups vs. Incumbents. Retrieved from: https://medium.com/@Emeka_Nwonu/the-next-innovation-wave-startups-vs-incumbents-e0267627b3d4

OECD (2017). Trust in peer platform markets. Consumer survey findings. Retrieved from: https://www.oecd-ilibrary.org/docserver/1a893b58-en.pdf?expires=1528113131&id=id&accname=guest&checksum=4103FBB13561669CD7948F9475D080B9

Öğüt, H., & Onur Taş, B. K. (2012). The influence of internet customer reviews on the online sales and prices in hotel industry. The Service Industries Journal, 32(2), 197-214.

Ohmae, K. (1983). *The mind of the strategist*. Harmondsworth: Penguin.

Olson, K. (2013). National study quantifies reality of the “Sharing Economy” movement.

Orcutt, M. (2017). What the hell is an initial coin offering? Retrieved from: https://www.technologyreview.com/s/608799/what-the-hell-is-an-initial-coin-offering/

Orcutt, M. (2018). States that are passing laws to govern smart contracts have no idea what they are doing. Retrieved from. https://www.technologyreview.com/s/610718/states-that-are-passing-laws-to-govern-smart-contracts-have-no-idea-what-theyre-doing/

O'Rourke, N., Psych, R., & Hatcher, L. (2013). *A step-by-step approach to using SAS for factor analysis and structural equation modeling*. Sas Institute.

Oskam, J., & Boswijk, A. (2016). Airbnb: the future of networked hospitality businesses. *Journal of Tourism Futures*, *2*(1), 22-42.

Ovans, A. (2015). What is a business model. *Harvard Business Review.*

Parr, (2015). Newsweek in 1995: Why the Internet Will Fail. Retrieved from: https://thehustle.co/clifford-stoll-why-the-internet-will-fail

Pazaitis, A., Kostakis, V., & Bauwens, M. (2017). Digital economy and the rise of open cooperativism: the case of the Enspiral Network. *Transfer: European Review of Labour and Research*, *23*(2), 177-192.

Peters, G. W., & Panayi, E. (2016). Understanding modern banking ledgers through blockchain technologies: Future of transaction processing and smart contracts on the internet of money. *Banking Beyond Banks and Money,* 239-278.

Peugh, J. L., & Enders, C. K. (2004). Missing data in educational research: A review of reporting practices and suggestions for improvement. *Review of educational research*, *74*(4), 525-556.

Piekarska, M. (2018). A way forward with open source and Blockchain. Retrieved from: https://jaxenter.com/way-forward-open-source-blockchain-141611.html

Pilkington, M. (2016). 11 Blockchain technology: principles and applications. *Research handbook on digital transformations*, 225.

Piscini, E., Guastella, J., Rozman, A., & Nassim, T. (2016). Blockchain: Democratized trust: Distributed ledgers and the future of value. Retrieved from: https://www2.deloitte.com/insights/us/en/focus/tech-trends/2016/blockchain-applications-and-trust-in-a-global-economy.html?id=us%253A2sm%253A3li%253Adup3039%253Aawa%253Acons%253A022516%253Att16%253Aauthoralumni

Pointcheval, D., & Stern, J. (2000). Security arguments for digital signatures and blind signatures. *Journal of cryptology*, *13*(3), 361-396.

Porter, M. (1990). *The Competitive Advantage of Nations*. NY: Free Press

Porter, M.E. (1979). How Competitive Forces Shape Strategy. *Harvard Business Review, 57*(2), 137-145.

Porter, M. E., & Millar, V. E. (1985). How information gives you competitive advantage. Harvard Business Review, 63(4), 149-160.

PR Newswire (2018) CryptoBnB Announces New Partnerships and Provides Update. Retrieved from: https://www.prnewswire.com/news-releases/cryptobnb-announces-new-partnerships-and-provides-update-300597964.html

Puschmann, T., & Alt, R. (2016). Sharing economy. *Business & Information Systems Engineering, 58*(1), 93-99.

PwC (2015). "The Sharing Economy." PwC Consumer Intelligence Series. https://www.pwc.com/us/en/technology/publications/assets/pwc-consumer-intelligenceseries-the-sharing-economy.pdf

PwC (2017). UK sharing economy to get $8bn boost in 2017. Retrieved from: https://www.pwc.co.uk/who-we-are/regional-sites/northern-ireland/press-releases/P2P.html

Quattrone, G., Proserpio, D., Quercia, D., Capra, L., & Musolesi, M. (2016). Who benefits from the sharing economy of Airbnb? In *Proceedings of the 25th international conference on world wide web*, 1385-1394.

Rafii, F., & Kampas, P. J. (2002). How to identify your enemies before they destroy you. *Harvard Business Review*, *80*(11), 115-23.

Rampell, A (2015). DISTRIBUTION V INNOVATION. Retrieved from: http://www.arampell.org/2015/11/04/distribution-v-innovation/

Ranzini, G., Newlands, G., Anselmi, G., Andreotti, A., Eichhorn, T., Etter, M., ... & Lutz, C. (2017). Millennials and the Sharing Economy: European Perspectives.

Raskin, M., & Yermack, D. (2016). Digital currencies, decentralized ledgers, and the future of central banking. *National Bureau of Economic Research,* w22238.

Rauch, D. E., & Schleicher, D. (2015). Like Uber, but for local governmental policy: The future of local regulation of the "Sharing Economy." *George Mason Law & Economics*.

Redman, J. (2018). Meet Cryptocribs a Rental Service That Aims to Decentralize Airbnb. Retrieved from: https://news.bitcoin.com/meet-cryptocribs-a-rental-service-that-aims-to-decentralize-airbnb/

Reinartz, W.J., Haenlein, M. & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of Market Research*, *26*(4), 332-344.

Richter, N. F., Sinkovics, R. R., Ringle, C. M., & Schlaegel, C. (2016). A critical look at the use of SEM in international business research. *International Marketing Review*, *33*(3), 376-404.

Ringle, C. M., & Spreen, F. (2007). Beurteilung der Ergebnisse von PLS-Pfadanalysen. *Das Wirtschaftsstudium*, *36*(2), 211-216.

Rogers, C. R. (1962). The interpersonal relationship. *Harvard Educational Review*, *32*(4), 416-429.

Rogers, E. M. (2010). *Diffusion of innovations*. NY: Simon and Schuster.

Rosic, A. (2016). Smart Contracts: The Blockchain Technology That Will Replace Lawyers. Retrieved from: https://blockgeeks.com/guides/smart-contracts/

Rosic, A. (2017). What is a Cryptocurrency Wallet? Retrieved from: https://blockgeeks.com/guides/cryptocurrency-wallet-guide/

Ross, S. (2017) Whatever Happened to the Internet's Promise? Retrieved from: https://techonomy.com/2017/03/whatever-happened-to-the-internets-promise/

Rysman, M. (2009). The economics of two-sided markets. *Journal of Economic Perspectives, 23*(3), 125-43

Rysman, M., & Schuh, S. (2017). New innovations in payments. *Innovation Policy and the Economy*, *17*(1), 27-48.

S., L (2015). How bitcoin mining works. Retrieved from: https://www.economist.com/the-economist-explains/2015/01/20/how-bitcoin-mining-works

Sapienza, P., & Zingales, L. (2012). A trust crisis. *International Review of Finance*, *12*(2), 123-131.

Sarstedt, M., Ringle, C. M., Henseler, J., & Hair, J. F. (2014). On the emancipation of PLS-SEM: A commentary on Rigdon (2012). *Long range planning, 47*(3), 154-160.

Saumure, K., & Given, L. M. (2008). Convenience sample. *The Sage encyclopedia of qualitative research methods*, 125-126.

Sawyer, A. G., & Page Jr, T. J. (1984). The use of incremental goodness of fit indices in structural equation models in marketing research. *Journal of Business Research*, *12*(3), 297-308.

Schafer, C. (2017). A short story about how Airbnb funded their startup with cereal boxes. Retrieved from:https://medium.com/@austincoleschafer/a-short-story-about-how-airbnb-funded-their-startup-with-cereal-boxes-ac6e62cf4c4c

Schiller, B. (2018). On This Blockchain-Based Version Of Airbnb, There's No Middleman. Retrieved from: https://www.fastcompany.com/40524021/on-this-blockchain-based-version-of-airbnb-theres-no-middleman

Schmidt, G. M., & Druehl, C. T. (2008). When is a disruptive innovation disruptive? *Journal of product innovation management*, *25*(4), 347-369.

Scholz, T. (2016b). *Platform cooperativism. Challenging the corporate sharing economy*. New York, NY: Rosa Luxemburg Foundation.

Schor, J. (2016). Debating the Sharing Economy. *Journal of Self-Governance & Management Economics*, *4*(3).

Schor, J. B., & Fitzmaurice, C. J. (2015). 26. Collaborating and connecting: the emergence of the sharing economy. *Handbook of research on sustainable consumption*, *410*.

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of educational research*, *99*(6), 323-338.

Schumacker, R. E. (2004). Rasch measurement: The dichotomous model. *Introduction to Rasch measurement*, 226-257.

Sedgwick, K. (2018). 46% of Last Year's ICOs Have Failed Already. Retrieved from: https://news.bitcoin.com/46-last-years-icos-failed-already/

Seth, S. (2018) Public, Private, Permissioned Blockchains Compared. Retrieved from: https://www.investopedia.com/news/public-private-permissioned-blockchains-compared/

Seidel, M. D. L. (2018). Questioning Centralized Organizations in a Time of Distributed Trust. *Journal of Management Inquiry*, *27*(1), 40-44.

Seidel, M. D. L., & Greve, H. R. (2017). *Emergence: How novelty, growth, and formation shape organizations and their ecosystems*. In *Emergence* (pp. 1-27). UK: Emerald Publishing Limited.

Shallcross, J. (2018). Finding a luxury vacation might be easier than you thought. Retrieved from: https://edition.cnn.com/travel/article/luxury-vacation-rentals-airbnb/index.html

Shapero, A., & Giglierano, J. J. (1982). *Exits and entries: A study in yellow pages journalism* (p. 2). , Ohio State University, College of Administrative Science.

Sheedy, C. (2018) Blockchain: the future of record keeping. Retrieved from: https://www.intheblack.com/articles/2018/03/22/blockchain-future-record-keeping

Shermin, V. (2017). Disrupting governance with blockchains and smart contracts. *Strategic Change*, *26*(5), 499-509.

Schreiber, J. B., Nora, A., Stage, F. K., Barlow, E. A., & King, J. (2006). Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of educational research*, *99*(6), 323-338.

Shmueli, G. (2010). To explain or to predict? *Statistical science*, 289-310.

Siddiqi, F. (2017). Smart Property and Smart Contracts. Retrieved from: https://blog.siddiqi.info/smart-property-smart-contracts/

Siegler, M., G. (2011). Airbnb Cozies Up To Facebook To Help You Feel More At Home When Away From Home. Retrieved from: https://techcrunch.com/2011/05/09/airbnb-social-connections/

Snoj, B., Pisnik Korda, A., & Mumel, D. (2004). The relationships among perceived quality, perceived risk and perceived product value. *Journal of Product & Brand Management*, *13*(3), 156-167.

Solow, R. M. (1957). Technical Change and the Aggregate Production Function. *Review of Economics and Statistics*. 39, 312-20.

Soska, K., Kwon, A., Christin, N., & Devadas, S. (2016). Beaver: A Decentralized Anonymous Marketplace with Secure Reputation. *IACR Cryptology ePrint Archive*, 464.

SSB (2017a). Handler privat innkvartering på nett. Retrieved from: https://www.ssb.no/teknologi-og-innovasjon/artikler-og-publikasjoner/en-av-ti-handler-privat-innkvartering-via-nett

SSB (2017b). Flere innenlandsreiser i 2017. Retrieved from: https://www.ssb.no/transport-og-reiseliv/artikler-og-publikasjoner/flere-innenlandsreiser-i-2017

SSB (2018). Befolkningen. Retrieved from: https://www.ssb.no/befolkning/faktaside/befolkningen

Statista (2018b). Quarterly average daily rate of hotels in New York in 2016 and 2017 (in U.S. dollars) Retrieved from: https://www.statista.com/statistics/202391/average-daily-rate-of-hotels-in-new-york/

Statista (2018c). Change revenue per available room in the United States lodging industry from 2005 to 2019. Retrieved from: https://www.statista.com/statistics/195709/percentage-of-change-in-revpar-in-the-us-since-2005/

Statista (n.d.a). Share of people who have heard of, signed up for, or actively used sharing economy services in Norway in 2015, by service. Retrieved from: https://www.statista.com/statistics/858353/knowledge-and-usage-of-sharing-economy-services-norway/

Statista (n.d.b). Vacation Rentals - Europe. Retrieved from: https://www.statista.com/outlook/268/102/vacation-rentals/europe#

Statista (n.d.c). Vacation Rentals - America. Retrieved from: https://www.statista.com/outlook/268/109/vacation-rentals/united-states#

Statista (n.d.d). Size of the blockchain technology market worldwide from 2016 to 2021 (in million U.S. dollars). Retrieved from: https://www.statista.com/statistics/647231/worldwide-blockchain-technology-market-size/

Stead, J. G., & Stead, W. E. (2013). The coevolution of sustainable strategic management in the global marketplace. *Organization & Environment*, *26*(2), 162-183.

Steiger, J. H. (2007). Understanding the limitations of global fit assessment in structural equation modeling. *Personality and Individual differences*, *42*(5), 893-898.

Stigler, G. J. (1971). The theory of economic regulation. *The Bell journal of economics and management science*, 3-21.

Stinchcombe, A. L. (1965). *Social structure and organizations*. In J. G. March (Ed.). Chicago: Rand McNally.

Sundararajan, A. (2014). Peer-to-peer businesses and the sharing (collaborative) economy: Overview, economic effects and regulatory issues. *Written testimony for the hearing titled The Power of Connection: Peer to Peer Businesses*.

Sundararajan, A. (2016). *The sharing economy: The end of employment and the rise of crowd-based capitalism.* Cambridge, MA: Mit Press.

Sullivan, G. M., & Artino Jr, A. R. (2013). Analyzing and interpreting data from Likert-type scales. *Journal of graduate medical education*, *5*(4), 541-542.

Swan, M. (2015*). Blockchain: Blueprint for a new economy*. O'Reilly Media, Inc.

Szabo, N. (1997). The idea of smart contracts. *Nick Szabo's Papers and Concise Tutorials*, *6*.

Taddeo, M. (2009). Defining trust and e-trust: from old theories to new problems. *International Journal of Technology and Human Interaction*, *5*(2), 23.

Tapscott, D. (2016). Blockchain - The Key To Powering Prosperity? Retrieved from: https://www.huffingtonpost.com/don-tapscott/blockchain---the-key-to-p_b_10537540.html

Tapscott, D., & Tapscott, A. (2016). Blockchain Revolution: How the technology behind Bitcoin is changing money, business, and the world. London, UK: Penguin

Tasca, P., & Ulieru, M. (2016). Blockchain as an Institutional Technology Spearheading an Equitable Exchange Economy.

Taylor, R. G. (1989). The role of trust in labor-management relations. *Organization Development Journal*, *7*(2), 85-89.

Taylor, S. (2015). Blockchain: understanding the potential. *Barclays Bank, July*, 1-5.

Teece, D. J. (2010). Business models, business strategy and innovation. *Long range planning*, *43*(2-3), 172-194.

Teece, D. J. (2017). Business models and dynamic capabilities. *Long Range Planning, 51*(1), 40-49.

Tellis, G. J. (2006). Disruptive technology or visionary leadership? *Journal of Product Innovation Management, 23*(1), 34-38.

The Economist. (2015). The promise of the blockchain. The trust machine. Retrieved from: https://www.economist.com/news/leaders/21677198-technology-behind-bitcoin-could-transform-how-economy-works-trust-machine

The Economist Intelligence Unit (2017). The election that everyone lost. Retrieved from: http://country.eiu.com/article.aspx?articleid=1955520979&Country=United%20Kingdom&topic=Politics&subtopic=Forecast&subsubtopic=Election+watch

Thomas, L. (2017). Airbnb just closed a $1 billion round and became profitable in 2016. Retrieved from: https://www.cnbc.com/2017/03/09/airbnb-closes-1-billion-round-31-billion-valuation-profitable.html

Thomond, P., Herzberg, T., & Lettice, F. (2003). Disruptive innovation: removing the innovators dilemma. In: Knowledge into Practice—BAM Annual Conference, Harrogate, UK.

Thompson, B. (2004). *Exploratory and confirmatory factor analysis: Understanding concepts and applications*. American Psychological Association.

Ting, D. (2016). Airbnb's Latest Investment Values It as Much as Hilton and Hyatt Combined. Retrieved from: https://skift.com/2016/09/23/airbnbs-latest-investment-values-it-as-much-as-hilton-and-hyatt-combined/

Tomsky, A (2018) Decentralization 2.0: Beyond the semi-monopolies of Uber and Airbnb. Retrieved from: https://thenextweb.com/contributors/2018/01/21/decentralization-2-0-beyond-semi-monopolies-uber-airbnb/

Toshi (2017) Introducing Toshi. Retrieved from: https://blog.toshi.org/introducing-token-2f2ceeab6d4c

Trushler, M. (2018). Is Blockchain Really A Disruptive Technology? Retrieved from: https://www.forbesmiddleeast.com/en/is-blockchain-really-a-disruptive-technology/

Tushman, M. L., & Anderson, P. (1986). Technological discontinuities and organizational environments. *Administrative science quarterly*, *31*(3), 439-465.

Tussyadiah, I. P., & Pesonen, J. (2016). Impacts of peer-to-peer accommodation use on travel patterns. *Journal of Travel Research*, *55*(8), 1022-1040.

Ullman, J. B., & Bentler, P. M. (2012). *Structural equation modeling* (2nd Edition). Handbook of Psychology.

Utterback, J. (1994). Mastering the dynamics of innovation: how companies can seize opportunities in the face of technological change. *Long Range Planning,*

Varma, A., Jukic, N., Pestek, A., Shultz, C. J., & Nestorov, S. (2016). Airbnb: Exciting innovation or passing fad?. *Tourism Management Perspectives*, *20*, 228-237.

Vaughan, R., & Hawksworth, J. (2014). *The sharing economy: How will it disrupt your business*. London: PriceWaterhouseCoopers.

Volgger, M., Pforr, C., Stawinoga, A. E., Taplin, R., & Matthews, S. (2018). Who adopts the Airbnb innovation? An analysis of international visitors to Western Australia. *Tourism Recreation Research*, 1-16.

von Kohorn, D. (2018). Blockchain Oracles Will Make Smart Contracts Fly. Retrieved from: https://hackernoon.com/oracles-help-smart-contracts-resolve-subjective-events-d81639d8291c

Wallenstein, J., & Shelat, U. (2017). Hopping Aboard the Sharing Economy. Retrieved from: https://www.bcg.com/publications/2017/strategy-accelerating-growth-consumer-productshopping-aboard-sharing-economy.aspx

Walport, M. G. C. S. A. (2016). Distributed ledger technology: beyond block chain. UK Government Office for Science. Retrieved from: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/492972/gs-16-1-distributed-ledger-technology.pdf

Wang, C., & Zhang, P. (2012). The evolution of social commerce: The people, management, technology, and information dimensions. *Communications of the Association for Information Systems, 31*(1), 105–127.

Ward, M. (2018). How Today's Tech Giants are Beating Startups at Their Own Game. Retrieved from: https://thinkgrowth.org/the-innovators-surfing-dilemma-skipping-a-paradigm-56a0bd98cf08

Wark, M. (2014). Digital Labor and the Anthropocene. DIS Magazine. Retrieved from: http://dismagazine.com/disillusioned/discussion-disillusioned/70983/mckenzie-wark-digitallabor-and-the-anthropocene/

Weber, T. A. (2014). Intermediation in a sharing economy: insurance, moral hazard, and rent extraction. *Journal of Management Information Systems, 31*(3), 35-71.

Webster, J., & Watson, R. T. (2002). Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly*, *26*(2), xiii–xxiii.

Weise, E. (2017). Airbnb rentals in San Francisco may dive with new host rules. Retrieved from: https://www.usatoday.com/story/tech/news/2017/05/01/airbnb-san-francisco-settlement-regulations-illegal-homeaway/101168688/

West, S. G., Finch, J. F., & Curran, P. J. (1995). Structural equation models with nonnormal variables: Problems and remedies.

Whitby, P. (2018). CryptoCribs, the new cool kid on the blockchain block. Retrieved from: https://www.eyefortravel.com/mobile-and-technology/cryptocribs-new-cool-kid-blockchain-block

Whittaker, T. A. (2012). Using the modification index and standardized expected parameter change for model modification. *The Journal of Experimental Education, 80*(1), 26-44.

Williamson, O. E. (1979). Transaction-cost economics: the governance of contractual relations. *The journal of Law and Economics, 22*(2), 233-261.

Williamson, O. E. (1981). The economics of organization: The transaction cost approach. *American journal of sociology, 87*(3), 548-577.

Wilmoth, J. (n.d.). What is an Altcoin? Retrieved from: https://www.ccn.com/altcoin/

Winkler, N., & Matthies, B. (2018). *FinTech and Blockchain–Keep Bubbling? Or Better Get Real*? In Digital Marketplaces Unleashed. Berlin: Springer.

Wothke, W. (1993). Nonpositive definite matrices in structural modeling. *Sage Focus Editions*, *154*, 256-256.

Wright, K. B. (2005). Researching Internet-based populations: Advantages and disadvantages of online survey research, online questionnaire authoring software packages, and web survey services. *Journal of computer-mediated communication*, *10*(3), JCMC1034.

Wright, A., & De Filippi, P. (2015). Decentralized blockchain technology and the rise of lex cryptographia.

Wörner, D., Von Bomhard, T., Schreier, Y. P., & Bilgeri, D. (2016). The Bitcoin Ecosystem: Disruption Beyond Financial Services?

Yermack, D. (2017). Corporate governance and blockchains. *Review of Finance*, *21*(1), 7-31.

Yin, R. K. (2009). *Case study research: Design and methods (applied social research methods*). London and Singapore: Sage.

Yin, R. K. (2013). Validity and generalization in future case study evaluations. *Evaluation*, *19*(3), 321-332.

Yli-Huumo, J., Ko, D., Choi, S., Park, S., & Smolander, K. (2016). Where is current research on blockchain technology? —a systematic review. *PloS one*, *11*(10), e0163477.

Yu, D., & Hang, C. C. (2010). A reflective review of disruptive innovation theory. *International journal of management reviews*, *12*(4), 435-452.

Zainudin, A. (2010). Research methodology for business and social science. *Shah Alam: Universiti Teknologi Mara Publication Centre (UPENA)*.

Zervas, G., Proserpio, D., & Byers, J. (2015). A first look at online reputation on Airbnb, where every stay is above average.

Zheng, H., Li, D., & Hou, W. (2011). Task design, motivation, and participation in crowdsourcing contests. *International Journal of Electronic Commerce*, *15*(4), 57-88.

Zhu, F., & Zhang, X. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of marketing*, *74*(2), 133-148.

Zimmerman, D. W. (1994). A note on the influence of outliers on parametric and nonparametric tests. *The journal of general psychology*, *121*(4), 391-401.

Zyskind, G., Nathan, O., & Pentland, A. (2015). Decentralizing Privacy: Using Blockchain to Protect Personal Data, Security and Privacy Workshops IEEE, 180-184.

Appendix 1: Overview of Acronyms

AVE	Average Variance Extracted
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CI	Confidence Interval
CR	Composite Reliability
DApps	Decentralized Applications
df	Degrees of Freedom
EFA	Exploratory factor analysis
ICO	Initial Coin Offering
MI	Modification Indices
MLE	Maximum Likelihood Estimation
PCFA	Pooled Confirmatory Factor Analysis
Q-Q	Quantile-Quantile
RMSEA	Root mean square error of approximation
SEM	Structural Equation Modeling
TLI	Tucker-Lewis Index
VIF	Variance Inflation Factor
$\chi 2$	Chi-squared

Appendix 2: Survey

Your use of sharing applications

In the upcoming questions, we will ask you to answer questions regarding your use and experience with sharing economy services.

1. Have you previously used **a sharing service** (home-sharing, ride-sharing, clothes-sharing, food-sharing)? * (Conditional question, respondents who replies «no» are directed to question 8)
   a. Yes
   b. No

Your use of sharing applications

2. Have you previously **used Airbnb**, or other **home-sharing services?**
   a. Yes, as a host
   b. Yes, as a guest
   c. Yes, both as a host and guest
   d. No

3. **How often** have you **used Airbnb** or other **home-sharing services** in the past **two** years?

	Never used	1-3 times	4-6 times	7-9 times	10 or more times
a. As a host					
b. As a guest					

4. Which of these **other sharing services** did you **use** in **2017**?

	Did not use	1-3 times	4-6 times	7-9 times	10 or more times
Uber, Lyft, BlaBlaCar or similar					
TaskRabbit, Zaarly or similar					
Second-hand or clothes sharing					

5. **Consider the following statements about your experience with sharing services:**

	1 - Strongly Disagree	2	3	4	5	6	7 - Strongly Disagree
I have good experiences using sharing services							

Q7 is a conditional question to respondents who replies 3 or less on question 6 .

6. Please complete the following sentence:

I do not have a good experience with sharing services because I...

(Select all that applies)

Think the services are hard to use/understand
Think it takes to much time to make an account
Have experienced to not be verified as a user
Do not trust the companies behind the services
Do not trust strangers online
Feel I do not get enough information about the persons I transact with
Do not wish to share my belongings
Do not wish to lend strangers' belongings
Am worried about my own safety
Am scared my assets will be damaged
Prefer to transact with traditional businesses
Am afraid my personal information will be taken advantage of
Have been swindled/scammed
Other

Your use of sharing applications

7. Please complete the following sentence:

I have not used sharing services because I...

(Select all that applies)

Think the services are hard to use/understand
Think it takes to much time to make an account
Have experienced to not be verified as a user
Do not trust the companies behind the services
Do not trust strangers online
Feel I do not get enough information about the persons I transact with
Do not wish to share my belongings
Do not wish to lend strangers' belongings
Am worried about my own safety
Am scared my belongings will be damaged
Prefer to transact with traditional businesses
Am afraid my personal information will be taken advantage of
Have not felt the need to
Other, please specify

Information security and safety in sharing platforms

Now we will ask you to consider the usefulness of insight to different information parameters regarding your meeting with actors in sharing services.

8. Imagine a situation where **you are going on a weekend trip to a big European city**, and are going to rent an **apartment/house/room** through a platform where private residences are rented out (e.g. Airbnb). How valuable would it be for you to gain **insight** to the following information **about the host**?

	1 - Useless	2	3	4	5	6	7 - Very useful
Full name							
Hometown							
Portrait picture							
Verified identification							
Personal description							

Personal characteristics							
Reviews from other sharing services (e.g. Task Rabbit, Uber)							
Reviews from former guests							
Average response time							
Language							
Relationship status							
Educational background							
Employment Record							
Criminal record							
Political orientation							
Credit score							
Social Media Accounts							
History from Netflix, Spotify, etc.							
References							

9. Imagine you are now going to **rent a room/apartment/house**, **WITHOUT** having Airbnb (or other platforms) **as an intermediary**. How important is the following factors to make such a **landlord attractive**?

	1 - Not Important	2	3	4	5	6	7 - Very Important
The host has a good reputation							
The host offers a low price							
The host is similar to myself							
The host is easy to contact							

The host presents detailed information about himself (as in the above question)							
The host offers simple and secure payment solutions							
The host offers good insurance schemes							

Your experience with sharing services

10. **Consider the following statements regarding your trust in online sharing services:**

	1 - Strongly Disagree	2	3	4	5	6	7 - Strongly Agree
I feel equally safe when I use sharing services as traditional actors							
I trust people I transact with in sharing services							
I trust the institution (eg Airbnb) behind the sharing platform							
I usually search for more info (eg via Google) on the people I transact with							

11.

	1 - Strongy Disagree	2	3	4	5	6	7 - Strongly Agree
I think online reviews often are fake							
I do not like the fact that sharing platforms utilize my data history for commercial interests							

12. If you could chose some **improvements for today's sharing services** (e.g. Airbnb), what would be **most important** of the following:

	1 - Not Important	2	3	4	5	6	7 - Very Important
Verification of the host's information about themselves from an external source							
More safety around payment systems							
More insurance/guarantees for the assets that are shared							
Possible to pay with cryptocurrencies							
Enhanced privacy regarding sharing and utilized personal information							

About you

At last, we wish to ask you some questions about yourself. You will be kept anonymous, and the information you give will only be used to give context to your other responses.

13. How old are you?

    Less than 18
    18-25 years
    26-35 years
    36-45 years
    46-60 years
    Over 60 years

14. What is your gender?

    Male
    Female
    Other

15. What is the most accurate description of the location of your current residence?

    Urban area/Big city
    Smaller city
    Rural areas/Country side

16. Where do you currently live?
17. What describes your current relationship status?

    Single
    Domestic relationship
    In a relationship
    Married
    Widow/Widower

18. What most accurately describes your current profession?

19. What was your income in 2017 (before taxes)?

    0-50 000 NOK
    50 001 - 200 000 NOK
    200 001 - 350 000 NOK
    350 001 - 600 000 NOK
    600 001 - 800 000 NOK
    800 000 - 1 000 000 NOK
    > 1 000 000 NOK

20. What is the highest level of education you have achieved (including ongoing studies)?

    Primary school
    High School
    College
    Bachelor Degree
    Masters Degree
    PhD - Doctoral Degree

Other, please specify

21. **Consider the following statements about yourself:**
I consider myself as ...

	1 - Strongly Disagree	2	3	4	5	6	7 - Strongly Agree
Open to trying new products/services							
Quick to adopt technological innovations							
Supportive of entrepreneurial companies							

22. **I consider myself as ...**

	1 - Strongly Disagree	2	3	4	5	6	7 - Strongly Agree
Slightly afraid of high-technological solutions							
Sceptical towards ideas I don't immediately understand							

23. **I am...**

	1 - Strongly Disagree	2	3	4	5	6	7 - Strongly Agree
Interested in cryptocurrencies (e.g bitcoin, ether, litecoin)							
Interested in information security							

(cryptography, computer crime, privacy)

24. **I consider myself as...**
You should rate the extent to which the pair of traits applies to you, even if one characteristic applies more strongly than the other.

	1 - Strongly Disagree	2	3	4	5	6	7 - Strongly Agree
Extraverted, enthusiastic.							
Critical, quarrelsome.							
Dependable, self-disciplined.							
Anxious, easily upset.							
Open to new experiences, complex.							
Reserved, quiet.							
Sympathetic, warm.							
Disorganized, careless.							
Calm, emotionally stable.							
Conventional, uncreative.							

Appendix 3: Q-Q plots of variables deviating from the normal distribution