Social and Economic Values on Peer-to-Peer Platforms

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Abstract

Both our economy and our society experience continuous digitization throughout the 21st century, which has facilitated the emergence and continued growth of digital platforms. Today, a variety of platform-based peer-to-peer business models shape the e-commerce landscape. Within the socio-economic crucible of peer-to-peer platforms, understanding and examining the interplay of social and economic values, user representation, and user behavior constitutes a challenging research endeavor. A structured literature review on the blueprint for peer-to-peer platforms (i.e., Airbnb) conceptualized open research questions that have been tackled by the thesis at hand. The central part of the thesis reports on four studies. The first online experiment focuses on how social and economic value expectations guide transaction intentions and how these are connected to the transaction partner's user representation. Next, a laboratory experiment investigates how user representation impacts actual behavior across multiple transactions. The subsequent scenario-based online survey answers the question if, in light of "trust-free" systems, trust-fostering user representation becomes obsolete. Last, the presence of peer-to-peer platforms causes societal issues. Whether tax compliant behavior on peer-to-peer platforms constitutes a moral obligation and guides transaction partner choice is the focus of the last online experiment. The thesis concludes with an outlook and pathways for future research.

Acknowledgements

First, I would like to thank my "family" of the last three years—the colleagues at the Institute of Information Systems and Marketing at the Karlsruhe Institute of Technology, many of whom have become friends: Anke, Armin, Bent, Christian, Frederik, Jan, Michael, Patrick, Peyman, Philipp, Simon—thank you for ensuring that I can look back on an enjoyable dissertation period. Beyond, I thank Benedikt and Florian for a great time as an affiliated researcher of the "Rocket Science Fiction Lab." Next, I thank Prof. Dr. Christof Weinhardt for the supervision and the opportunity to pursue my dissertation. Great thanks go to Prof. Dr. Timm-Christopher Teubner for his continuous advice and guidance. Further, I thank Prof. Dr. Christoph Michael Flath and Dr. Matthias Hauser, who guided me on the path of science. I also thank Prof. Dr. Alexander Mädche for his constant support.

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Finally, my special thanks go to Miriam. Your love and belief in me have carried me through the challenging time of finishing this dissertation, and I never want to be without them ever again.

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Acronyms

AFF	Affective Trust
AVE	Average Variance Extracted
CB	Covariance-Based
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
CMB	Common Method Bias
COG	Cognitive Trust
CR	Composite Reliability
df	Degrees of Freedom
DTT	Disposition to Trust
EEV	Expected Economic Value
EFA	Exploratory Factor Analysis
ELM	Elaboration Likelihood Model
ESV	Expected Social Value
FAM	Familiarity
HTMT	Heterotrait-Monotrait
INR	Intention to Rent
IS	Information Systems
ITB	Intention to Book
MC	Manipulation Check
MGA	Multi-Group Analysis
MN	Moral Norms
MU	Monetary Units
P2P	Peer-to-Peer
PLS	Partial Least Squares
PP	Profile Photos
RMSEA	Root Mean Square Error of Approximation
SD	Standard Deviation
SEM	Structural Equation Modeling
SR	Star Ratings
SRMR	Standardised Root Mean Square Residual
TBL	Trust in Blockchain
TBU	Trust in Blockchain User
TIP	Trust in Provider
TPE	Trust in Peers
TPL	Trust in Platform
TPR	Trust in Product
UR	User Representation
VIF	Variance Inflation Factor

Chapter 1

Introduction

1.1 Motivation

Both our economy and our society experience continuous digitization throughout the 21st century, which has facilitated the emergence and continued growth of digital platforms. Today, these platforms represent an integral part of the e-commerce landscape (Mittendorf, Berente, and Holten, 2019; Zimmermann et al., 2018; European Commission, 2016). As part of this emerging "platform economy," we have seen the birth of the "sharing economy" (Sundararajan, 2016; Teubner and Hawlitschek, 2018), where underutilized resources are effectively shared among users. Peer-to-peer (P2P) sharing platforms represent one of the most successful and fastest-growing business models (Mittendorf, Berente, and Holten, 2019; Zimmermann et al., 2018). While the European Commission already identified annual spendings of €27.9bn within the EU on these platforms in 2016 (European Commission, 2016), Mastercard and Kaiser Associates (2019) expect P2P platforms to generate a worldwide gross volume of US$455bn by 2023—doubling their 2018 gross volume.

The prime example of a successful P2P platform is the accommodation sharing platform Airbnb. As of July 2020, the platform offers more than 7 million listings from over 220 countries and claims to have already completed 750 million transactions since its foundation in 2008.[1] Additionally, Airbnb practically constitutes the blueprint for a whole category of new business models within the platform economy, shaping the standards for web design, transaction processing, and both social and behavioral norms. Though there are numerous other examples of P2P sharing platforms from the fields of car (e.g., Drivy) and ride-sharing (e.g., BlaBlaCar, zimride), resale (e.g., Etsy, eBay) or crowdwork (e.g., TaskRabbit), they all have one common objective: Creating transactions by matching supply and demand in the form of providers and consumers. The process of a P2P transaction itself, however, differs from traditional e-commerce in two key aspects.

First, both the supply side (provider) and the demand side (consumer) are commonly represented by non-professional private individuals—without an established brand image or global recognition. Therefore, unlike in transactions with established companies, consumers particularly face additional economic exposure caused by potential unreliability or fraudulent offers (AirbnbHell, 2019). At the same time, the transactions are subject to an inherent information asymmetry, as only the providers can assess the actual quality

[1] https://news.airbnb.com/fast-facts/

of the offer (e.g., an accommodation's condition). This aspect is particularly decisive, considering that in almost every P2P transaction, private individuals interact with each other for the first time (Ke, 2017b; Teubner, 2018). These conditions render one value particularly important for the realization of transactions—trust, the quintessence of the P2P platform economy (Gebbia, 2016; Hawlitschek, Teubner, and Weinhardt, 2016; Möhlmann and Geissinger, 2018). On the ride-sharing platform BlaBlaCar, for instance, consumers literally put their lives into the hands of their transaction partners (i.e., the driver).

Second, as transactions on P2P platforms can grant access to resources within providers' privacy spheres, a part of the transaction may take place offline, in the real world. For instance, conducting a transaction on an accommodation sharing platform leads to a real-world interaction with the respective provider, who may even be present throughout the entire duration of the stay (co-usage sharing). Thus, in addition to their asset or service, providers and consumers themselves become an inherent part of the transaction. The resulting personal interactions extend the transaction by an additional social facet. Nevertheless, because of the transaction's extension to providers privacy sphere, common P2P platform designs require consumers to request transactions from providers. In contrast to ordinary e-commerce, where consumers can purchase offered services or commodities directly, a transaction on these platforms takes place only if the provider agrees to this transaction request in an additional step. Consequently, for the formation of a transaction, both providers *and* consumers need to market themselves on the platform (Tussyadiah, 2016b; Karlsson, Kemperman, and Dolnicar, 2017).

From a conceptual point of view, P2P platforms can be classified by two dimensions (see Figure 1.1). First, by the mode of bringing together providers and consumers. This can be either exogenous, that is, determined by the platform itself (e.g., Uber) or endogenous, whereby providers and consumers themselves form transaction dyads on the platform (e.g., Airbnb). Second, by the degree of transactionality, that is, the degree of both sides' personal exposure within the transaction. While on platforms like eBay or Etsy, provider and consumer presumably never meet in the real world, the level of exposure is inevitably higher on platforms like Blablacar or Airbnb, on which offline interaction constitutes an integral part of the transaction.

To facilitate transactions between providers and consumers, platform operators have established a broad variety of artifacts (e.g., star ratings, profile photos, labels) for user representation (UR) (Abrahao et al., 2017; Dann, Teubner, and Weinhardt, 2019). Platform users can leverage these artifacts to build and maintain a reputation and present themselves as a trustworthy transaction partner. Overall, creating a trustworthy environment and maintaining a high level of trust between users is arguably the most decisive challenge platform operators face (Hawlitschek, Teubner, and Gimpel, 2018; Hawlitschek, Teubner, and Weinhardt, 2016; Mittendorf, Berente, and Holten, 2019). Strategies for implementing these trust-building UR artifacts, also called trust cues, in turn, highly depend on each cue's individual characteristics. Trust cues themselves, however, differ systematically in their mode of obtaining (e.g., by evaluations of previous transaction partners) and their content (e.g., text of a self-description) (Hesse et al., 2020). The individual characteristics of each trust cue determine how users perceive them, respond to them, and, ultimately, adapt their behavior.

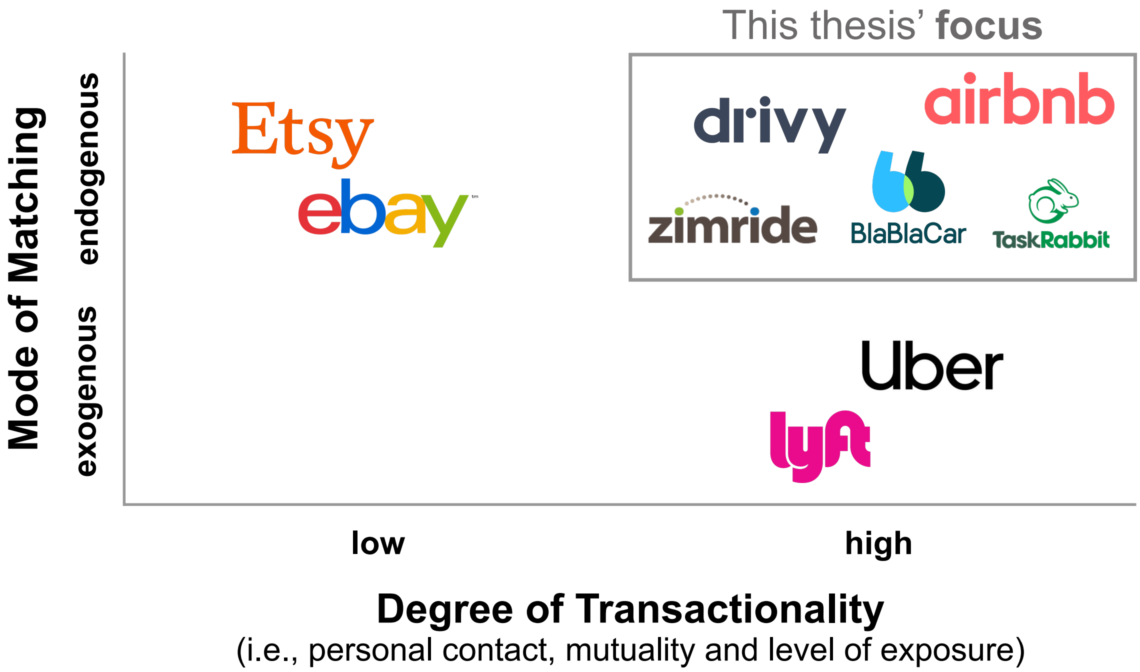

Figure 1.1: Delineation of P2P platforms, based on Dann et al. (n.d.)

Against this backdrop, present literature is still inconclusive regarding the influence of different types of trust cues on consumer behavior. Questions arise concering the dynamic interplay of different types of trust cues—an aspect that is particularly relevant for nascent platforms, struggling with reaching a critical mass of transactions without an established trust and user base (Hodapp, Hawlitschek, and Kramer, 2019). Moreover, platform designs based on new technologies such as the blockchain challenge existing assumptions about the overall need for trust cues. Blockchain has already been described as the technology that could render trust between users obsolete and promise to establish trust by design (Lundy, 2016; Glaser, 2017). However, empirical evaluations of this strong claim are scarce.

Moreover, the existence of P2P platforms raises societal questions. The present lack of a uniform transnational-applicable taxation regulation of P2P transactions allows providers to evade income taxes. Consequently, providers benefit from unfair competitive advantages over established business models, such as the hotel industry (OECD, 2019). In the US, for instance, less than 25% of all Airbnb providers comply with applicable tax regulations (Bibler, Teltser, and Tremblay, 2019). In this context, it remains unclear whether consumers are even aware of providers' tax behavior, whether it constitutes a tangible value in the selection of transaction partners, and whether this process is strictly economically-driven or constitutes a moral decision.

Summarizing, the overarching objective of the thesis at hand is to develop a comprehensive understanding of the economics of P2P platforms—with a focus on social and economic value dimensions in the initiation and conduction of transactions. This objective resonates with the following research agenda.

1.2 Research Agenda and Research Questions

This thesis raises four individual research questions. First, it is essential to generally understand the interplay of both social and economic value and UR. Anticipating a P2P transaction, which will include an offline, real-world experience, renders providers' UR on the platform highly relevant for consumers (Ert, Fleischer, and Magen, 2016; Fagerstrøm et al., 2017; Krasnova, Veltri, and Günther, 2012). Research on how the different UR artifacts affect consumers' perception of individual providers is still limited and inconclusive regarding the influence of social value. The question remains open, whether or not, economic considerations predominantly frame transaction intentions and how the presence of different UR artifacts affect either social or economic expectations. Hence, the first research question is:

RQ1: *How do different UR artifacts facilitate co-usage transactions through social and economic value?*

However, while the overall influence of social and economic values is inevitably necessary to understand how transactions on P2P platforms emerge in general, examining behavior within transactions requires the consideration of further aspects. As prior literature has already shown, P2P platforms implement a variety of trust cues within URs to foster trust between strangers. In this regard, present literature has commonly agreed that the effect of these trust cues' are predominantly stable (McKnight, Choudhury, and Kacmar, 2002; Mcknight, Cummings, and Chervany, 1998) or steadily increasing (Cabral and Hortaçsu, 2010) across several transactions. Nevertheless, the seminal Elaboration Likelihood Model (ELM) by Petty and Cacioppo (1986) challenges these assumptions by arguing that the type of trust cues determines whether its influence is rather stable or temporary. To explore the presumably varying effect of different trust cues over time (i.e., across multiple transactions), the next research question states:

RQ2: *How does the interplay of cognitive and affective trust cues affect trusting behavior in sharing transactions over time?*

Beyond the mere examination of trust within transactions on P2P platforms, the influence of a platform's technological foundation on trusting perceptions represents another interesting facet. Since technological environments that enable platforms (e.g., the Internet) have already shown to be a vital antecedent for trust in providers on the platform, the question arises whether the blockchain may induce similar effects. While the blockchain is generally attributed to affect trust (Beck, 2018), the question of whether consumers perceive it as a technology that renders trust among platform users obsolete, remains open. To shed light on the trusting relationships in blockchain-enabled environments, the next research question is:

RQ3: *How do blockchain-enabled platforms frame consumers' trust perception and their intention to enter a transaction?*

Although the platform economy has written several success stories, some of its business models can be linked to emerging economic and societal problems. In this manner, P2P accommodation sharing, for instance, is increasingly being discussed in the same breath with problems such as over-touristification (Oskam and Boswijk, 2016), ever-increasing rent prices (Gurran and Phibbs, 2017), and illegal hospitality operations (Schäfer and Braun, 2016). One contributing factor to all these problems is existing tax evasion by providers on the platform (OECD, 2019). Recalling the importance of mutual trust among transaction partners, providers suspected to evade taxes may find themselves confronted with mistrust from prospective consumers. Since tax behavior is not observable for consumers today, the question arises whether providers may benefit from indicating tax compliance, for instance, by leveraging a visual label in their UR. To disentangle these relationships, the next research question states:

RQ4$_a$: *How does the presence of a tax compliance label affect consumers' trust towards and, in turn, their intentions to book at the tax-compliant provider?*

Beyond the mere influence on the transaction intention, questions arise regarding the composition of the effect of tax compliance. Because of its extensive impact on society as a whole, tax compliance is a controversial issue. Public budgets directly linked to tax compliance elevate tax compliance to a societal and even moral obligation. Since personal moral norms are, in general, a determinant of economic decisions (Frey and Torgler, 2007; Antonetti and Anesa, 2017), the question arises whether they also guide the choice of the P2P transaction partner. Consequently, the second part of this research question is:

RQ4$_b$: *How do individual moral norms moderate the effect of tax compliance labels?*

1.3 Thesis Structure

This thesis covers five chapters (Figure 1.2). Following this introductory chapter, Chapter 2 provides the scientific foundation for this thesis by including the paper "*Poster child and guinea pig – insights from a structured literature review on Airbnb.*" The study represents the first published structured literature review on the prominent blueprint for P2P platforms and summarizes the scientific findings of 118 highly diverse articles.

Chapter 3, the main part of this thesis, reports on four studies on the social and economic values on P2P platforms. Chapter 3.1, "*Where the host is part of the deal: Social and economic value in the platform economy,*" consists of an online experiment that examines how individual UR artifacts facilitate transactions through consumers' expectation of social and economic value. To answer Research Question 1, the study considers UR artifacts that either provide personal information, stem from exogenous sources, or entail both of these aspects.

Chapter 3.2, "*On the dynamics of cognitive and affective trust cues: Behavioral evidence from a peer-to-peer sharing platform experiment*," is, at present, submitted to the second round of revision at the *Journal of the Association for Information Systems*. Within a laboratory experiment, the study investigates the interplay of cognitive and affective trust cues on trusting behavior across multiple P2P transactions. The study answers Research Question 2.

Chapter 3.3, "*Blockchain and Trust in the Platform Economy: The Case of Peer-to-Peer Sharing*," sheds light on blockchain-based P2P sharing platforms using an scenario-based online survey. Answering Research Question 3, this study investigates how the presence of the blockchain as a P2P platform's technological layer impacts consumers' trusting perception, transaction intention, and whether it renders further trust cues on the platform obsolete.

Chapter 3.4, "*How do Tax Compliance Labels Impact Sharing Platform Consumers? An Empirical Study on the Interplay of Trust, Moral, and Intention to Book*," examines the existence of P2P platforms from a societal perspective. The study is currently submitted to the *Business & Information Systems Engineering* journal. To answer Research Question 4, the study investigates the role of tax compliance for platform users by employing an online experiment. In light of current policy debates about the taxation of P2P platform transactions, the study investigates whether tax compliance is a relevant factor for choosing transaction partners on P2P platforms and whether this constitutes a matter of morality.

Last, Chapter 5 summarizes the results of this thesis and elaborates on future research potential.

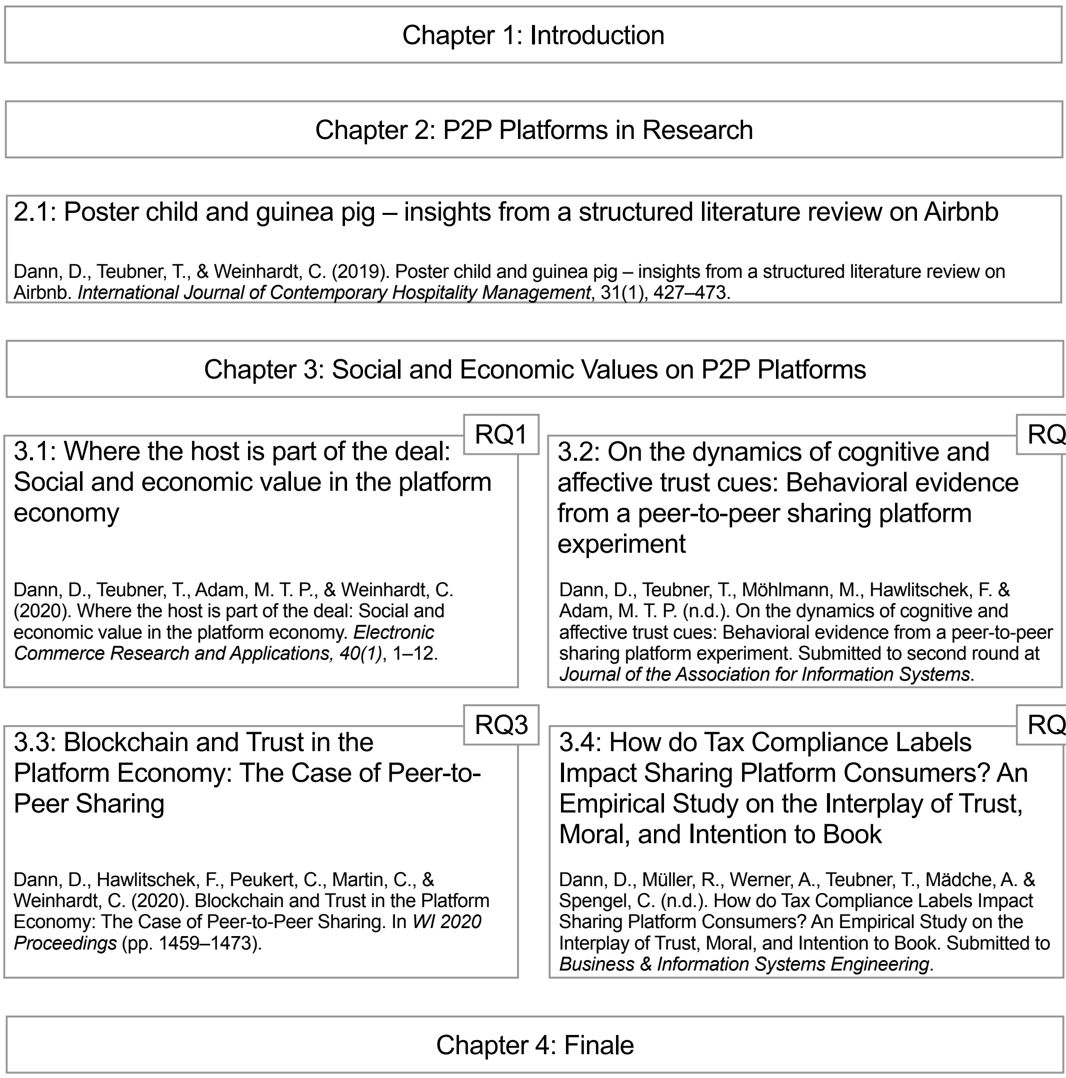

Figure 1.2: Thesis structure and overview of publications

Chapter 2

P2P-Networks in Research

2.1 Poster child and guinea pig—insights from a structured literature review on Airbnb

To provide an adequate understanding of P2P platforms per se, this chapter includes a structured literature review of the platform, which represents the blueprint for a variety of other P2P business models—Airbnb. The literature review shows that research on Airbnb is highly diverse in terms of domains, methods, and scope; motives for using Airbnb are manifold (e.g., financial, social and environmental); trust and reputation are considered crucial by almost all scholars; the platform's variety is reflected in prices; and the majority of work is based on surveys and empirical data while experiments are scarce.

David Dann, Timm Teubner & Christof Weinhardt[1]

2.1.1 Introduction

A growing body of research from various domains investigates questions revolving around the accommodation sharing platform Airbnb. With over three million listings in almost any country worldwide, Airbnb has grown to be the most important peer-based platform for accommodation sharing (Airbnb, 2018). Ten years after its foundation in 2008, Airbnb's market evaluation ranges in the league of large hotel groups and metasearch platforms such as Expedia and Booking.com (Forbes, 2017; McDermid, 2017). Airbnb operates a two-sided market, matching supply (providers) and demand (consumers) for peer-based accommodation. The variety offered through the platform is large, including urban apartments, guest rooms and vacation homes—and also more exotic listings such as tree houses, castles, igloos, and houseboats (Forbes, 2016). Airbnb addresses both private and business customers and facilitates everything from day trips to stays of several months (Mittendorf and Ostermann, 2017). The platform's role as a marketing channel is undeniable, as hosts generate an average additional income of $924 per month (Earnest, 2017). Importantly, platforms such as Airbnb enable access to a resource within the private sphere of the provider. Hence, these are required to deliberately accept incoming booking requests. Note that this constitutes a fundamental difference

[1]This study was published in the International Journal of Contemporary Hospitality Management, https://doi.org/10.1108/IJCHM-03-2018-0186, (Dann, Teubner, and Weinhardt, 2019).

to other accommodation platforms (e.g., Booking.com) and also to other C2C platforms (such as eBay). Further, it renders design artifacts of reputation management and user representation on Airbnb especially important as here, both providers and consumers need to market themselves (Tussyadiah, 2016b; Karlsson, Kemperman, and Dolnicar, 2017).

Airbnb's emergence has not gone unnoticed within the tourism, hospitality, and travel literature. Recent studies consider Airbnb's value proposition in comparison to "traditional" hotel offers, consumers' motives for choosing it (Guttentag et al., 2018; Lalicic and Weismayer, 2018; Tussyadiah and Park, 2018), and the platform's impact on the hotel industry (Akbar and Tracogna, 2018; Blal, Singal, and Templin, 2018; Cheng and Foley, 2018).

Overall, the literature on Airbnb has grown rapidly. A Google Scholar search for the keyword "Airbnb" yields 28,500 hits as of May 2018. Although the great majority of these references do not represent genuine research on Airbnb (but rather brief mentions), we believe that it is due time to take a step back and asses the current state of affairs. Given Airbnb's multifacetedness, it is not surprising that research on the platform comprises many domains, including Information and Management, Tourism/Travel/Hospitality, Law, and Economics. But also the platform itself and its technical, economic, social, and legal environments evolve frequently, fundamentally, and fast. This holds particularly true for legal aspects (e.g., changing municipal housing rules) and for the platform's mechanisms and design, as for instance illustrated by updates in the review system Airbnb (2014a) or the introduction of automated pricing regimes (Yee and Ifrach, 2019). Interestingly, such services are also offered by third-party providers (e.g., beyondpricing.com). In this regard, it is also not surprising that Airbnb operates its own multi-method, multi-perspective research team with some 100+ designers, data scientists, survey experts, and user experience specialists (Antin, 2016; Bion, Robert, and Goodman, 2017).

With this overview article, we attempt to provide a map of the broad research landscape around Airbnb. We identify common approaches, methods, findings, and—based on this—identify research gaps and derive opportunities for future work. To the best of our knowledge, this paper represents the first structured literature review on the diverse and complex topic of Airbnb and thus closes a research gap in and by itself. Despite Airbnb's relative novelty, there has emerged an accumulated body of research that needs analysis and synthesis. We bring together previously disparate streams of work, providing a holistic picture. In systematically outlining what already has been done and what has not, which methods have been used in which domains and in combination with which research objectives and foci, we enable the identification of advisable and promising directions for future work.

The remainder of this paper is structured as follows. In Chapter 2.1.2, we describe the steps of the literature review procedure and provide first descriptive statistics. In Chapter 2.1.3 and 2.1.4, we explore the Airbnb-related literature along the structure of conceptual themes. Last, in Chapter 2.1.5, we discuss our overarching findings and, based on this, present managerial implications and pathways for future work.

2.1.2 Method

The literature search and selection process follows common methodological suggestions (Webster and Watson, 2002). As the existing literature on Airbnb is highly interdisciplinary, we queried several databases (i.e., ACM Digital Library, AIS Electronic Library, EBSCOhost, Emerald Insight, IEEE Xplore Digital Library, ProQuest, ScienceDirect/Scopus, Web of Science) using the search term "Airbnb" in title, abstract, or keywords (Brocke et al., 2009). After removing duplicates, this yielded 243 articles. We then analyzed each article's title and abstract and excluded those that did not focus on Airbnb in particular. This concerned articles on the overall development of platform business models where in many of these cases, the paper refers to Airbnb in a sequence along with other platforms such as Uber. Moreover, in this step, we excluded redundant papers (e.g., multiple versions), early-stage drafts, and non-scientific publications (e.g., press releases). This resulted in a set of 86 articles. Following that, we conducted successive backward and forward search resulting in 32 additional relevant articles, yielding a total of 118. A summary of all articles is provided in Table 2.1.

Our literature review follows a concept-centric approach. To identify key concepts and themes, we started investigating an initial set of papers in conference proceedings and journals in the domains of tourism and information systems. We then independently identified a set of concepts to classify the articles. Subsequently, the set of concepts was synthesized and clarified by means of discussion. The identification process was primarily oriented toward ensuring that all concepts are sound, cohesive within, and sufficiently distinct between each other. Following the suggestions by Webster and Watson (2002), this set of concepts was adopted in the subsequent process of classification and synthesis. In a similar manner, the articles were classified with regard to method (e.g., experiment or survey), perspective (e.g., provider, consumer), and further aspects. The classification process was conducted by the involved authors independently. Again, discrepancies were discussed and resolved.

The identified themes relate to:

- *user motives and types* (i.e., which kinds of people use Airbnb and why; 45 studies);
- *reputation systems* (i.e., how are reputation and trust managed on Airbnb; 31 studies);
- *text reviews and self-descriptions* (i.e., what do Airbnb's write about themselves and other users; 21 studies);
- *profile images* (i.e., which role does imagery play for interaction and which types of photos are used; 9 studies);
- *prices and pricing* (i.e., how are listings priced, which factors entail economic value; 27 studies);
- *economic and media impact* (i.e., how did the emergence of Airbnb impact the hotel industry, local housing markets, and how has it been reflected in the popular press; 17 studies); and

- *legal and regulatory aspects* (i.e., where does Airbnb get in conflict with existing law, how may regulation be developed, how are cities dealing with the platform; 18 studies).

Table 2.1: Literature overview

Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Varma et al. (2016)	×					×		Investigation of importance of different factors for Airbnb users and non-users. While many factors exhibit similar importance, differences are found in the importance of security, cleaning, loyalty programs, and recommendations. Executives of large hotels do not fear Airbnb, smaller businesses do.	×		Survey, Interviews	347, 12	202 US cities	TOURISM
Lutz et al. (2018)	×							Characteristic distinction of guests who frequently stay in a shared room and those who prefer to stay in an entire home.	×		Survey, Empirical	659, 500	5 US Cities	INF-MAN
Bae et al. (2017)	×		×					Before a trip, consumers purchase intention is influenced by social distance, credibility of reviews, review breadth, information usefulness, and adoption of reviews. After a trip, perceived information discrepancy influences travelers' willingness to share their trip experience.	×		Survey	411	South Korea	INF-MAN
Cheng and Foley (2018)	×	×	×					Evaluation of rating, rating volume, review, information quality, and media richness on intention. Perceived value and satisfaction are determinants of intention to buy. Rating volume, review, information quality, and media richness are important precursors.	×		Survey	280	-	INF-MAN
Dann et al. (2018)	×	×	×					Proposal of research model and scenario-based online experiment design for explaining guests' intention to book by their perceived social and economic value and how those are reflected in hosts' user representation.	×		Survey	-	-	INF-MAN
Guttentag and Smith (2017)	×							Airbnb consumers consider the platform as a substitute for especially mid-range hotels. In terms of traditional hotel attributes, Airbnb consumers have high expectations of the service.	×		Survey	844	Canada	TOURISM
Guttentag et al. (2018)	×							Consumers are mostly attracted by Airbnb's practical and experiential attributes. Motives: Interaction, home benefits, novelty, sharing economy ethos, local authenticity. Cluster analysis identifies Money Savers, Home Seekers, Collaborative Consumers, Pragmatic Novelty Seekers, and Interactive Novelty Seekers.	×		Survey	844	Canada	TOURISM

Table 2.1: Literature overview

Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Hamari, Sjöklint, and Ukkonen (2016)	×							Participation in collaborative consumption (CC) is driven by the user motives sustainability, enjoyment, and economic benefits, partly mediated through attitude (toward CC).	×		Survey	168	Worldwide	INF-MAN
Hawlitschek, Teubner, and Weinhardt (2016)	×							Differentiation and evaluation of motives for and against peer-to-peer sharing, differentiated for providers and consumers. Development of measurement model. Main drivers include enjoyment in sharing, social factors, economics benefits. Deterrents include process risk, privacy and effort concerns, and independence through ownership.	×	×	Survey	61, 605	GER	INF-MAN
Karlsson, Kemperman, and Dolnicar (2017)	×			×				Exploration of drivers for host decisions of accepting or rejecting guests. Refusing a guest is a common behaviour of hosts in peer-to-peer networks. The decision is affected by both trip-related attributes and (guests') personal characteristics.		×	Survey	192	Australia	TOURISM
Lalicic and Weismayer (2018)	×							Analysis of influencing factors of consumers' Airbnb loyalty. While social and authentic experiences are antecedents of consumers' loyalty to Airbnb, perceived economic benefits and perceived reduce risk exhibit no significant impact.	×		Survey	557	Worldwide	TOURISM
Lee and Kim (2018)	×							The effect of hedonic and utilitarian values on satisfaction and loyalty of Airbnb users. Airbnb users' hedonic value has a positive impact on satisfaction and loyalty, while utilitarian value influences only on satisfaction. Product involvement is a moderator.	×		Survey	511	US	TOURISM
Liang, Choi, and Joppe (2018b)	×							Relationship between satisfaction, trust and switching intention, repurchase intention in the context of Airbnb. Trust was found as a mediator between transaction-based satisfaction and repurchase intention. Trust in Airbnb did not affect trust in hosts.	×		Survey	395	Canada, US	TOURISM
Liang, Choi, and Joppe (2018a)	×							Survey on consumer repurchase intention, which is found to be affected by perceived value, perceived risk, electronic word of mouth, perceived authenticity, and price sensitivity.	×		Survey	395	Canada, US	TOURISM

Table 2.1: Literature overview

Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Liu and Mattila (2017)	×							2 (high vs. low power) x 2 (belongingness vs. uniqueness appeal) design to measure click through and purchase intentions for an Airbnb advertisement. The high power framing exhibits higher purchase intentions for the uniqueness ad, the low power framing exhibits higher purchase intentions for the belongingness ad.	×		Survey	139	US	TOURISM
Malazizi, Alipour, and Olya (2018)	×							Survey on Airbnb hosts reveals that financial, safety, and security risk negatively influence hosts' satisfaction. Financial, safety, security, and political risks negatively influence continuance intention to use; and psychological risk increases satisfaction, continuance intention to use, and intention to recommend. Satisfaction positively affects continuance intention to use and intention to recommend.		×	Survey	221	Cyprus	ECON
Mao and Lyu (2017)	×							Investigation of repurchase intention based on the TPB. Attitude and subjective norms emerge as determinants of repurchase intention while PBC does not. Perceived value and risk impact customer attitude.	×		Survey	624	US	TOURISM
Mittendorf and Ostermann (2017)	×							Trust is a positive and perceived risk a negative direct antecedent of hosts' willingness to accept a customer on Airbnb. Business travelers are perceived to be more trustworthy than private travelers.		×	Survey	53	-	INFMAN
Mody, Suess, and Lehto (2017)	×							Comparative assessment of hotels and Airbnb. Serendipity, localness, communities, and personalization represent valuable experience economy constructs. Airbnb appears to outperform the hotel industry in the provision of all experience dimensions.	×		Survey	630	US	TOURISM
Möhlmann (2015)	×							Survey on the determinants of using a sharing option again: Satisfaction intention to use (again) are driven by utility, trust, cost savings, and familiarity.	×		Survey	187	GER	INFMAN
Pezenka, Weismayer, and Lalicic (2017)	×							Comparison of Airbnb users' personalities with Airbnb-nonusers reveals that, based on the Big Five personality traits, Airbnb users score significantly higher on openness, extraversion, agreeableness, and conscientiousness.	×		Survey	1.426	Worldwide	TOURISM

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Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Poon and Huang (2017)	×							Effects of traveler personality and trip properties on intention to use Airbnb. Airbnb users and non-users express few differences in their demographics and perceived importance of accommodation attributes.	×		Survey	248	Hong Kong	TOURISM
Priporas et al. (2017)	×							Convenience and assurance are critical contributors to the measurement of service quality in remote Airbnb lodgings.	×		Survey	202	Worldwide	TOURISM
Stollery and Soo (2017)	×							South Korean Airbnb guests perceive monetary savings, hedonic benefits, and novelty as antecedents and psychological risk as a deterrent of perceived value.	×		Survey	410	South Korea	INFMAN
Teubner and Hawlitschek (2018)	×							Investigation on how privacy concerns affect a (potential) provider's intentions to share accommodation via different channels. Privacy concerns are largest for "intermediate" audiences (sufficiently large, still personal connection, e.g., social media platforms).		×	Survey	237	GER	INFMAN
Tussyadiah (2015)	×							Exploratory study on drivers and deterrents of collaborative consumption in travel. Drivers are societal aspects of sustainability and community, and economic benefits. Deterrents are lack of trust, lack of efficacy with regard to technology, lack of economic benefits.	×		Survey	754	US	TOURISM
Tussyadiah (2016a)	×							Exploration of satisfaction drivers with P2P accommodation: Enjoyment, monetary benefits, accommodation amenities. Social benefits influence guest satisfaction for the private room category but not for entire homes/apartments.	×		Survey	644	US	TOURISM
Yang and Ahn (2016)	×							Enjoyment, reputation, and perceived security are found to be antecedents of attitude towards Airbnb. Sustainability and economic benefit exhibit no significant influence. Attitude towards Airbnb positively affects loyalty towards Airbnb.	×		Survey	294	South Korea	INFMAN
Young, Corsun, and Xie (2017)	×						×	Investigation of driving factors of P2P usage and influencing factors in preferring a P2P option over a hotel. P2P usage is motivated by leisure travel. Price, location, dwelling size, trip length and size of the tour group are the most influential factors.	×		Survey	788	Denver	TOURISM

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Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Festila and Dueholm Müller (2017)	×							Analysis of consumer-object relationships. Identification of four types of Airbnb users: Outgoing, Pragmatic, Friend, Experience Seeker.	×		Interviews	13	-	INF-MAN
Ikkala and Lampinen (2014)	×	×			×			Interviews with hosts. These divert reputational capital into rental price and sometimes price their property below market level to choose their exchange partners from a wider pool of candidates.		×	Interviews	11	Helsinki	INF-MAN
Ikkala and Lampinen (2015)	×							Exploration of motives for hosts to participate in hospitality-exchange services. Main motives are financial and social reasons. While the presence of money often drives hosts to participate in Airbnb hosting, social factors tend to gain in importance over time.		×	Interviews	11	Helsinki	INF-MAN
Jung and Lee (2017)	×		×					Interviews with Airbnb and Couchsurfing hosts on the first phase of transaction initiation. While Couchsurfing hosts use these mainly for socializing, Airbnb hosts use them for risk assessment and reduction.		×	Interviews	12	Seoul	INF-MAN
Lampinen (2016)	×							Airbnb hosts see monetary benefits as a gateway for further social exchange and interpersonal interaction.		×	Interviews	12	San Francisco	INF-MAN
Wang and Nicolau (2017)	×							Airbnb hosts have non-economic motivation to bypass the platform, and they are able to overcome trust barriers through leveraging the unbundling of intermediary functions.		×	Interviews	10	China	INF-MAN
So et al. (2018)	×							Motivations and constraints of Airbnb consumers: Findings from a mixed-methods approach	×		Interview, Survey	8, 519	US	TOURISM
Tussyadiah and Park (2018)	×		×					Study on how Airbnb hosts present themselves online (well-traveled or of a certain profession). Well-traveled hosts are perceived more trustworthy and guests exhibit a higher willingness to book.	×	×	Empirical, Survey	31,119. 301	14 US cities	TOURISM

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Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Teubner (2018)	×							Social network analysis based on US-based Airbnb transactions/ reviews. Hosts and guests form a complex transactional network (giant component).	×	×	Empirical, SNA	100,572, 2.7M	44 cities Worldwide	WP
Ke (2017a)	×							Linking Airbnb listings to US Census data suggests that income represents a major driver for people to host on Airbnb. Entire home listings tend to be located in areas with higher income and receive more reviews.		×	Empirical	211.124	US	WP
Ke (2017b)	×	×	×					Quantitative description of Airbnb based on large-scale data set including room types, rating distributions (number, valence), word analysis, host types (e.g., multi-listers), and review growth.		×	Empirical	2.3M	Worldwide	WP
Li, Moreno, and Zhang (2015)	×				×			Linear regression of properties managed by professional and non-professional hosts. Properties of professional hosts have higher revenues (16.9%), higher occupancy rates (15.5%), and are less likely to exit the market (13.6%). Non-professional hosts are less likely to offer different rates across different dates based on underlying demand (e.g., due to major holidays or conventions).		×	Empirical	24.845	Chicago	WP
Tussyadiah (2016b)	×	×	×					Cluster analysis of Airbnb hosts based on their profile information. Identified archetypes are Global Citizen, Local Expert, Personable, Established, and Creative.		×	Empirical	12.785	NYC	TOURISM
Guttentag (2015)	×				×		×	Consideration of Airbnb's development through the lens of disruptive innovation theory. Motivations for using Airbnb include cost-savings, household amenities, and the potential for more authentic local experiences.	×		Conceptual	-	-	TOURISM
Kim, Yoon, and Zo (2015)	×	×						Conceptual model of service platforms as trusted third parties for reducing (perceived) risks. The proposed model for consumers' intention includes antecedents to trust, relative advantages, and perceived risk.	×		Conceptual	-	-	INF-MAN
Yannopoulou (2013)	×							Airbnb as a platform for user-generated brands with three emerging themes: access to private sphere, meaningful interpersonal interactions, and authenticity.			Conceptual	-	-	INF-MAN

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Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Neumann and Gutt (2017)		×			×			Theoretical model for setting optimal listing prices. Panel data analysis suggests that hosts react to receiving additional reviews, ID verification, and superhost status by increasing prices slightly (i.e., by 0.5% to 1.6%).		×	Theoretical Model, Empirical	143.405	8 US cities	INF-MAN
Abramova, Krasnova, and Tan (2017)		×			×			Conjoint choice analysis; Effects of trust cues on choice likelihoods /WTP equivalences; Star ratings (5 stars) with 1, 5, 15 (€27.76) reviews, ID verification (€17.72), and verified apartment photo (€12.57) have greatest impact, whereas host/guest similarity and social network have much lower or no impact.	×		Survey	450	GER	INF-MAN
Fagerstrøm et al. (2017)		×		×				Negative facial expression / absence of facial image reduces likelihood to rent. Reverse effect for neutral / positive facial expressions. Absence of facial image / angry facial expression cannot be compensated for by low prices or high rating.	×		Survey	139	-	INF-MAN
Mauri et al. (2018)		×	×					Personal reputation (e.g., ratings, photos) explains almost 40% of popularity variation of Airbnb listings (conceptualized as rating score, number of ratings, number of times saved to wishlist, superhost).	×		Survey	502	Italy, UK	TOURISM
Abrahao et al. (2017)		×						Online experiment (trust game) among Airbnb users recruited through the platform. Reputation systems increase trust between dissimilar users (i.e., high social distance). Actual market data suggests that transactions between users with high social distance are only facilitated by high host reputation.	×		Online Experiment, Empirical	8,906, 1M	US	ECON
Qiu and Abrahao (2018)		×	×					Online investment game with Airbnb users reveals that going from 4 to 5 stars as a host is equivalent to having 10 more reviews. Yet, the relative effectiveness of ratings and number of reviews differ on the reputation's differentiation power.		×	Online Experiment	5.277	US	INF-MAN

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Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Fradkin, Grewal, and Holtz (2018)		×						Two field experiments on Airbnb's reputation system. First, Airbnb guests are offered a $25 coupon to submit a review. Second, a simultaneous review system is implemented and tested. Both tweaks make the reputation system more informative.	×	×	Field Experiment	558,959, 15,470 + 15,759	-	WP
Ert, Fleischer, and Magen (2016)		×		×	×			Hedonic price regression on Airbnb listings indicates that more trustworthy photos lead to a higher prices and increased chances to purchase, whereas review scores do not exhibit sufficient variance. Review scores affect guests' decisions when varied experimentally.	×		Empirical, Survey	175, 566, 270	Stockholm, Israel, Israel	TOURISM
Chen and Xie (2017)		×			×			Hedonic pricing approach. Functional characteristics of Airbnb listings were significantly associated to the price of the listings, and that three of five behavioral attributes of hosts were statistically significant.		×	Empirical	5.779	Austin	TOURISM
Dai, Spasic, and Andres (2017)		×	×					Development of tool for transforming text reviews into a star rating (1 to 5 stars) using ordinary text processing and data mining methods.		×	Empirical	68.276	Boston	INFMAN
Edelman and Luca (2014)		×		×	×			Quantitative analysis of NYC-based listings and hosts using hedonic price models. Indication of "racial discrimination" against Afro-American hosts on Airbnb who charge approximately 12% less than other hosts for equivalent listings.		×	Empirical	3.752	NYC	WP
Fradkin (2015)		×						Study on the efficiency of Airbnb's search algorithm based on internal data. Removal of frictions is expected to lead to 102% of additional matches. A personalized ranking algorithm would increase matching rates by up to 10%.	×	×	Empirical	569.864	US	WP
Gunter (2018)		×						Examination of the relative importance of the 4 criteria for obtaining Superhost status. Star rating ¿ reliable cancellation behavior ¿ responsiveness ¿ sufficient Airbnb demand. Commercial Airbnb providers are more likely to receive Superhost status.		×	Empirical	17,356, 16,696	San Francisco	TOURISM
Gutt and Herrmann (2015)		×			×			Difference-in-difference analysis of listings with and without visible star rating. Hosts with visible star rating price their listing €2.60 higher than hosts of comparable listings without visible star rating.		×	Empirical	14.871	NYC	INFMAN

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Gutt and Kundisch (2016)		×			×			Empirical analysis of the review sub-dimension "value" on listing price shows that guests react to price changes with awarding lower ratings particularly in the value dimension.		×	Empirical	14.859	NYC	INF-MAN
Lee (2015)		×			×			Linear regression exploration of features associated with room sales: Price, minimum stay, amenities, host responsiveness, wish list, number of reviews, membership seniority. Not so critical for room sales: Overall rating, number of references.		×	Empirical	4.178	5 US cities	INF-MAN
Liang et al. (2017)		×			×			Investigation of superhost badges. Guests are willing to pay more and submit higher ratings for listings provided by superhosts.		×	Empirical	3.830	Hong Kong	TOURISM
Martin-Fuentes et al. (2018)		×			×			Application of a Support Vector Machine to classify listings on Airbnb within the 1-5 Hotel-star categories. The classifier is trained with hotel data from Booking.com.		×	Empirical	NA	World-wide	TOURISM
Sanchez-Vazquez, Silva, and Santos (2017)		×						Introduction of a recommender system for Airbnb listings.			Empirical	15.000	NYC, London	INF-MAN
Teubner and Hawlitschek (2018)		×						Development of Airbnb rating scores over time. Lower rated listings exhibit higher dropout rates. Overall rating score skewness is also governed by other phenomena (e.g., regression to the mean, law of large numbers).		×	Empirical	43.288	Berlin	INF-MAN
Teubner, Hawlitschek, and Dann (2017)		×		×	×			Hedonic price regression models: Signals such as the hosts' rating scores, duration of membership, and Superhost status provide economic value. Also, conventional signals such as accommodation photographs consistently translate into price premiums.		×	Empirical	13.884	86 German cities	ECON
Xie and Zhenxing (2017)		×			×			Analysis of the impacts of quality and quantity attributes of Airbnb hosts on listing performance. Host quality attributes significantly influence listing performance through cue-based trust.		×	Empirical	5.805	Austin	TOURISM

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Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Zervas, Proserpio, and Byers (2015)		×						The majority of Airbnb properties (95%) have 4.5 or 5.0 star ratings and almost none have less than 3.5 stars. Comparison of listing available both on Airbnb and TripAdvisor reveals that highest ratings are more common on Airbnb.		×	Empirical	226.594	Worldwide	WP
Grbovic (2017)		×						Brief description of techniques used for search ranking at Airbnb, which is based on listing quality, location relevance, reviews, host response time as well as guest and host preferences and past booking history.		×	Conceptual	-	-	INF-MAN
Roelofsen and Minca (2018)		×						Conceptualization of how Airbnb uses both platform design mechanics and an influencing public representation to establish a self-regulated, biopolitics-controlled community.		×	Conceptual	-	-	ECON
Abramova et al. (2015)			×					Exploration and evaluation of different strategies for host in response to negative text reviews. The strategies confession, apology, and denial can improve future guests' trusting beliefs. If subject of criticism is beyond the host's control, denial does not increase trust, whereas confession and excuse still have positive effects.	×		Survey	320	GER	INF-MAN
Edelman, Luca, and Svirsky (2017)			×				×	Field experiment on Airbnb. Guests with distinctively African-American names are 16% less likely to be accepted than guests with distinctively White names.		×	Field Experiment	6.400	5 US cities	ECON
Ma, Neeraj, and Naaman (2017)			×					Empirical analysis of topics Airbnb hosts reveal in self-description. Hosts most frequently write about Origin/Residence, Work/Study, and Interests/Tastes. Survey on how trustworthy self-descriptions shows that perceived trustworthiness increases with profile length and number of topics mentioned. Choice experiment shows that perceived trustworthiness is a predictor of guests' host choice.		×	Empirical, Survey	40,005, 1,200, 355	12 US cities	INF-MAN
Alsudais (2017)			×					Manual labeling of Airbnb reviews; 85% of reviews include a reference to a host (either by paraphrasing or by name)		×	Empirical	1.024	3 US cities	INF-MAN

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Authors (Year)	Motives and types	Reputation and trust	Text	Photos	Prices	Economic impact	Legal and regulation	Approach	Consumers	Providers	Method	Sample	Origin	Domain
Bridges and Vásquez (2018)			×					Analysis of 21200 text reviews (for guests and hosts). These comprise a very restricted set of words and are mostly positive (93%). Further analysis reveals that less-than-positive experiences are communicated using subtle cues, for instance, by information that is excluded.	×	×	Empirical	400	4 US cities	TOURISM
Brochado, Troilo, and Shah (2017)			×					Semantic and relational text review analysis. A concept map comprising eight themes (stay, host, place, location, apartment, room, city, home) reveals that all themes are culturally universal, that is, can be observed across India, Portugal, and the US.	×	×	Empirical	1.776	India, Portugal, US	TOURISM
Camilleri and Neuhofer (2017)			×					Qualitative thematic analysis of text reviews from Airbnb listings in Malta, identifying six key components: Welcoming, expressing feelings, evaluating location and accommodation, helping and interacting, recommending, and thanking.	×		Empirical	850	Malta	TOURISM
Johnson and Neuhofer (2017)			×					Exploration of value co-creation experiences in Jamaica based on qualitative online content analysis of text reviews.	×	×	Empirical	942	Jamaica	TOURISM
Ma, Neeraj, and Naaman (2017)			×					Development of a computational framework to predict perceived trustworthiness of host profile texts. Host profiles were assessed by AMT workers with regard to trustworthiness. Examples for positive features are words from the categories "positive emotion" and "social."		×	Empirical	4,180/ 450	12 US cities	INFMAN
Phua (2018)			×					Analysis and conceptualization of negative reviews about Airbnb on business review platforms. Most of the negative reviews (27%) criticize problems with accessing a competent customer service agent. Others complain i.a. last-minute cancellation by hosts (21%), pricing/fee structure (14%), or misrepresentation (13%).	×		Empirical	664	-	TOURISM
Hoffen et al. (2017)			×					Comparison of sentiment scores of Airbnb reviews with those of #airbnb-tweeds. Overall, reviews exhibit more positive sentiment. Identification of positive/negative words in positive/negative reviews.			Empirical	20.000	Washington, Berlin	INFMAN

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Gunter and Önder (2017)				×	×			Regression analysis of Airbnb listings demand in Vienna reveals a price-inelastic demand structure. Listing size, number of photos, and host responsiveness positively drive demand. Listing price, distance to city center, and host's response time have negative impact.		×	Empirical	7.864	Vienna	TOURISM
Kakar et al. (2018)				×	×			Hispanic and Asian hosts exhibit 9.6% and 9.3% lower listing prices as compared to White hosts. No significant impact of gender and sexual orientation on price listings.		×	Empirical	715	San Francisco	WP
Rahimi, Liu, and Andris (2016)				×				Color scheme and interior ornateness analysis of Airbnb listings from cities around the world. Color schemes are found to be rather similar, whereas ornateness varies considerably depending on city, but also for different neighborhoods within cities.		×	Empirical	48,651, 2,095	6 US cities, 2 RU cities, 2 Asian cities	ECON
Zhang et al. (2016)				×	×			Comparison of listing performance, based on their representation on Airbnb. On average, listings with verified (i.e., implying high quality) room photos are 9% more frequently booked, yielding additional $2,455 in yearly earnings.		×	Empirical	17.826	7 US cities	INFMAN
Benítez-Aurioles (2018)					×			Investigation of the (counter-intuitive) negative correlation of price with flexible cancellation policies or instant book availability.		×	Empirical	497.509	44 cities Worldwide	TOURISM
Dudás et al. (2017)					×			Multi-band geographic visualization of Airbnb listings in Budapest (different colors for different properties: price, attractiveness, distance). No significant correlation between a listing's price and its location in Budapest in found.		×	Empirical	NA	Budapest	ECON
Gibbs et al. (2018a)					×			Hedonic price regression models on metropolitan areas in Canada. Economic value can be obtained by particular host and listing attributes.		×	Empirical	15.716	5 Canadian cities	TOURISM

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Gibbs et al. (2018b)					×			Empirical analysis of five Canadian metropolitan areas shows that across these markets the majority (52.2%) of Airbnb providers do not utilize dynamical pricing. Price fluctuation is more common for professional hosts, hosts with greater experience, entire homes, and listings in high demand markets.		×	Empirical	39.837	5 Canadian cities	TOURISM
Gutiérrez et al. (2017)					×	×		Airbnb accommodation distribution in Barcelona reveals a center-periphery pattern and capitalization of proximity to tourist attractions more than the hotel sector. Empirical data analysis identifies touristic areas that experience high pressure from Airbnb.		×	Empirical	14.539	Barcelona	TOURISM
Lécuyer, Tucker, and Chaintreau (2017)					×			Implementation of an Airbnb crawler, accessing listings in high frequency to derive insights on occupancy rates and revenues; by and large corroborating claims by Airbnb and prior studies (e.g., in 2014, 6% of hosts owned $\geq$3 listings but accounted for 37% of all revenues).		×	Empirical	NA	NYC	INFMAN
Wang and Nicolau (2017)					×			Empirical analysis of Airbnb data from 33 cities. Not only listing attributes but also host attributes have a significant effect on the price.		×	Empirical	180.533	33 cities Worldwide	TOURISM
Xie and Zhenxing (2017)					×	×		Empirical data analysis from 2008 to 2011. Airbnb supply (i.e., #listings) leads to a decline of local hotels' financial performance. Yet, increasing price difference between hotels and Airbnb listings and higher price dispersion of Airbnb listings can mitigate this effect		×	Empirical	1.482	Austin	TOURISM
Hill (2015)					×			Description of how Airbnb has developed, introduced, and improved its smart pricing algorithm.		×	Conceptual	-	-	INFMAN
Adamiak (2018)						×		Description of Airbnb supply in European cities		×	Empirical	737k	432 EU cities	TOURISM

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Blal, Singal, and Templin (2018)						×		Average prices of Airbnb rentals positively influence hotel sales performance patterns while average satisfaction of Airbnb users negatively affects them. Airbnb's effect on hotel sales performance patterns varies across different hotel segments. Yet, the total number of Airbnb listings is found to have a non-significant effect on hotel sales performance.		×	Empirical	101	San Francisco	TOURISM
Cheng and Foley (2018)						×		Analysis of online newspaper comments made in response to an article reporting Airbnb's new anti-discrimination policy (text-mining and co-stakeholder analysis)	×	×	Empirical	217	-	TOURISM
Constantiou, Eaton, and Tuunainen (2016)						×		Re-telling the Airbnb story based on blog entry analysis. Two phases in Airbnb's platform development are identified: 1) Creation of a network of users and 2) platform augmentation.			Empirical	813	-	INF-MAN
Fang, Ye, and Law (2016)						×		Empirical analysis of Airbnb/ sharing economy on TOUR-ISM industry employment, suggesting that a) the entry of Airbnb benefits the entire TOUR-ISM industry by generating new jobs as more tourists come due to the lower accommodation cost but b) low-end hotels are threatened and hence marginal effects decrease with increasing sharing economy size.		×	Empirical	657	Idaho	TOURISM
Gurran and Phibbs (2017)						×	×	Analysis of written submissions to a NSW inquiry on short-term renting and Airbnb inventory for the city of Sydney. Noise, nuisance, traffic, parking, and waste management issues arise when short-term holiday rentals penetrate residential areas.		×	Empirical	NA	Sydney	ECON
Horn and Merante (2017)						×		Investigation of the impact of Airbnb density on rental prices (tract-wise) for the city of Boston. An increase in Airbnb listings by one standard deviation is associated with an increase in asking rents of 0.4%.		×	Empirical	832	Boston	ECON
Schäfer and Braun (2016)						×	×	Empirical analysis reveals that 0.3% of accommodations in Berlin violate the misuse prohibition law (Zweckentfremdungsverbot). Considering individual neighborhoods, this number can be higher (up to 7.04% for Mitte), which indicates that there is more of a problem with individual sub-markets than a problem for the whole city		×	Empirical	11.495	Berlin	ECON

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Wegmann and Jiao (2017)						×	×	Regression analysis for Airbnb penetration in different US cities. Derivation of four principles for cities: Usage of web scraping to obtain data; booking patterns vary and necessitate micro-geographic regulation; need of enforcement; differentiation between host types.		×	Empirical	19.337	5 US cities	ECON
Zervas, Proserpio, and Byers (2017)						×		Empirical analysis of Airbnb's entry into the US state Texas. Lower-priced hotels are most affected by the rise of Airbnb.		×	Empirical	294.383	Texas	INF-MAN
Akbar and Tracogna (2018)						×		Consideration of Airbnb as a hybrid form of governance (including both market and hierarchy arrangements) based on transaction cost theory and platform economics			Conceptual	-	-	TOURISM
Lee et al. (2016)						×	×	The paper explores how short-term rentals affect prices and supply of affordable housing in Los Angeles, and how municipal policymakers can best regulate Airbnb, arguing for a 14% occupancy tax on any unit listed on the platform.		×	Conceptual	-	-	LAW
Llop (2017)						×	×	Analysis of Airbnb's negative influence on the city of Barcelona and it's corresponding regulatory measures.		×	Conceptual	-	-	ECON
Mikhalkina and Cabantous (2015)						×		Analysis of Airbnb's media coverage in six mainstream business publications between 2009 and 2013 reveals a three-staged process: From the first attempts to classify Airbnb into existing categories, over the approach of describing Airbnb as a separate phenomenon, up to the final acknowledgement of Airbnb as an iconic business model.			Conceptual	-	-	INF-MAN
Brauckmann (2017)							×	Combination of official statistical data with a geo-information system reveals no definitive impact of the sharing economy on housing markets.		×	Empirical	NA	Hamburg	TOURISM
Quattrone et al. (2016)							×	Identification of disparities in different municipal regulation of Airbnb. Utilization of public available Airbnb data to identify areas that benefit from its presence. Propose to introduce a municipal regulated transferable sharing right.		×	Empirical	17.825	London	INF-MAN

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Oskam and Boswijk (2016)							×	Outline of Airbnb's further development in the next years and Delphi panel discussion on the impact this development can have on the TOUR-ISM sector, hotel industry, and municipal government goals.			Delphi Panel	31	Amsterdam	TOURISM
Interian (2016)							×	Legal/regulatory analysis of issues between Airbnb and US cities. It is argued that Airbnb should be held liable for ensuring basic compliance by using measures similar to what has been implemented in many European cities.		×	Conceptual	-	-	LAW
Jonas (2015)							×	Examination of New York City's current regulation of common sharing scenarios. Instead of trying to squeeze companies within this domain into existing regulations, the city should develop individual sharing economy-specific regulations.		×	Conceptual	-	-	LAW
Lines (2015)							×	The paper explores options for Arizona municipalities to regulate Airbnb, where two alternatives are outlined. First, existing regulation may be used to govern Airbnb. Alternatively, it is argued that a new system addressing Airbnb's unique operations, benefits, and problems should be implemented.		×	Conceptual	-	-	LAW
O' Regan and Choe (2017)							×	Analysis of Airbnb from the perspective of cultural capitalism. Examination of Airbnb's impact on cultural, economic, political, and consumer-related contexts.		×	Conceptual	-	-	TOURISM
Santolli (2017)							×	Legal/regulatory analysis of issues between Airbnb and the city of Barcelona where officials have employed an unenforceable, ineffective de jure ban on Airbnb.		×	Conceptual	-	-	LAW
Stabrowski (2017)							×	Socio-economic effects and legal and regulatory implications of Airbnb; Identification of opportunities to align goals from Airbnb and local governments through "platform cooperativism" (e.g., by distributing annual dividends to all city residents).		×	Conceptual	-	-	ECON
Toto (2017)							×	Legal analysis on the role of lass action waivers and arbitration agreements in Airbnb's terms of use, which prevent legal enforcement against cases of racial discrimination. It is argued that without regulatory adaptions, such waivers threaten civil rights enforcement.		×	Conceptual	-	-	LAW

Note that this categorization is not disjunctive. Hence, each publication may be associated with more than one category and in fact, about one-third of all publication is multi-thematic in this regard.

Overall, the reviewed literature is methodologically diverse, for instance, based on surveys (37), interviews (8), empirical data (58), experiments (4) or conceptual work (17). Other less frequent methods are theoretical models, social network analysis, and Delphi panels. Note that these figures sum up to over 118 as some articles use more than one method. In terms of domains, most articles refer to Tourism/Travel/Hospitality (48) or Information and Management (42), while a smaller proportion falls into the domains of Economics (13), Law (6), or has working paper status (9). The vast majority of the reviewed articles was published in the past four years 2018 (25), 2017 (54), 2016 (21), and 2015 (15). Moreover, we find that most studies focus on North America (51), Europe (24), and Asia (9), while fewer use worldwide data (10) and only 5 studies consider different reference areas (e.g., the sample's origin) at the same time.

2.1.3 Airbnb in Research

Representing a poster child of the broader platform economy landscape, Airbnb has emerged as a frequently studied application, as it allows examination on both macroeconomic and socio-psychological levels. To provide some structure and overview, we use the seven identified themes to discuss, summarize, and synthesize the retrieved publications. First, we take a look at motives for people to use Airbnb in the first place (either as hosts, guests, or both). This stream of research naturally extends to the identification of different user types and their characteristics. Next, we consider the paramount factors of trust and reputation. As Airbnb deliberately "designs for trust" (Gebbia, 2016), these are reflected by a variety of artifacts such as star ratings, text reviews, self-descriptions and profile images. We then conflate research on how prices (on Airbnb) emerge, that is, the tangible economic value of various exogenous and user-related factors—and what this means for hosts' pricing decisions. Next, we review work on Airbnb's impact on the hotel industry and the housing market. We then take a look at work on how Airbnb has been received by the public and the media. Ultimately, we take a look at legal and regulatory aspects around Airbnb, including matters of housing legislation, taxation, liability, consumer protection and platform competition and data ownership.

User Motives and User Types

User Motives from the Consumer Perspective Very much in line with findings on user motives for adopting sharing platforms in general, research on Airbnb identifies a multiplicity of relevant motives, including economic, sustainability-related, and social aspects (Hamari, Sjöklint, and Ukkonen, 2016; Hawlitschek, Teubner, and Gimpel, 2016; Tussyadiah, 2016a). Taking a look at Airbnb's advertising, it becomes clear that the platform attempts to appeal in particular to users seeking social, local, unconventional, and authentic experiences (Airbnb, 2014b; Airbnb, 2015b). And in fact, from the consumers' perspective, beyond economic benefits, motives do include aspects such as community feeling and sustainability (Möhlmann, 2015; Tussyadiah, 2015; Guttentag et al., 2018). Interestingly, and despite the fact that Airbnb tends to attract consumers with high income, high education, high travel activity, and high tech affinity, cost savings still remain the dominant motive. Beyond conducive factors, impediments have been identified likewise, including lack of trust in other users (Hawlitschek, Teubner, and Gimpel, 2016), emphasizing the importance of the platform as a trusted third party for reducing risks (Kim, Yoon, and Zo, 2015).

Extending work on motives for initially adopting Airbnb, cost savings, utility, trust, perceived value, and familiarity are found to drive consumers to use the platform again (Möhlmann, 2015; Mao and Lyu, 2017; Liang, Choi, and Joppe, 2018b; Liang, Choi, and Joppe, 2018a). Specifically, user loyalty is found to be driven by hedonic value (Lee and Kim, 2018) and social and authentic experiences (Lalicic and Weismayer, 2018).

. . . and from the Provider Perspective While most published papers have considered motives from the consumer's (i.e., the guest's) perspective (31 studies), fewer studies focus on hosts (16 studies). The sizeable income opportunities for hosts ($924 per month on average) suggest that financial factors may play a paramount role (Earnest, 2017). Other studies suggest that hosts use Airbnb for both financial and social reasons (Ikkala and Lampinen, 2015). Interestingly, this holds true for "remote" hosts with fewer in-person interactions as well.

Consumer Types In view of the broad spectrum of products and applications, it is not surprising that Airbnb users differ in many ways. Guttentag et al. (2018), for instance, consider different types of guests based on the motives interaction, home benefits, novelty, sharing economy ethos and local authenticity. They find that people are attracted to Airbnb's practical (e.g., cost savings, convenient location, household amenities) rather than its experiential attributes (e.g., excitement, novelty, uniqueness). The authors cluster respondents into the five motivational segments money savers, home seekers, collaborative consumers, pragmatic novelty seekers, and interactive novelty seekers, where home seekers represent the largest group. Users from this cluster are usually older, more experienced, tend to book longer trips, entire homes, and travel as larger parties and significantly more likely with children. Pragmatic novelty seekers, in contrast, are more likely to rent entire homes while collaborative consumers tend to rent co-used accommodations. Further, they tend to have Airbnb experience both as guests and hosts. From a platform's perspective, such user typologies enable a better understanding of its users and afford apposite targeting and marketing approaches.

In addition, Airbnb users differ from non-users in general. With regard to personality traits, they score higher on conscientiousness, extroversion, agreeableness, and openness (Pezenka, Weismayer, and Lalicic, 2017). Other studies report differences with regard to consumer-object relationships (Varma et al., 2016; Festila and Dueholm Müller, 2017; Poon and Huang, 2017). While some consumers prefer a personal experience, expressed through a reflection of the host's personality in the accommodation, others favor a cleaner, more hotel-like experience. In terms of expectations regarding personalization and further aspects such as serendipity, localness, and communities, Airbnb surpasses traditional hotel offers (Mody, Suess, and Lehto, 2017). Furthermore, compared to users who book traditional hotels, Airbnb users are found to put less importance on factors such as security or housekeeping (Festila and Dueholm Müller, 2017).

Host Types Also from the hosts' perspective, there are found different clusters (e.g., global citizen, local expert, personable, established, creative) which differ in self-presentation, communication behavior, pricing, and hosting frequency (Tussyadiah, 2016b). While all archetypes are distinguished by their textual self-description, important factors such as acceptance rates, response rates, and guest evaluations are comparable across clusters. However, "established" hosts exhibit slightly lower response rates, higher response time, lower prices, and higher rating scores.

Importantly, Airbnb hosts exhibit different behaviors depending on whether they leverage the platform in a professional or non-professional way. In several cities, professional hosts (i.e., those who offer more than one listing) account for more than half of all available listings (Table A.1). For instance, professional hosts generate higher revenues and have higher occupancy rates (Li, Moreno, and Zhang, 2015; Gibbs et al., 2018a). Likewise, professional hosts are early adopters, their listings tend to be entire apartments rather than private rooms, and they are more likely to be located within cities (Ke, 2017b). On the listing's page, professional hosts use the self-description section for listing advertising purposes rather than for describing themselves personally. Importantly, professional hosts are perceived as being more trustworthy (Tussyadiah and Park, 2018).

Airbnb hots also differ from those on other accommodation sharing platforms. Couchsurfing hosts consider a prospective guest's online representation as a supportive and friendship-forming tool while Airbnb hosts focus on risk assessment (Tussyadiah and Park, 2018).

Reputation Systems and Trust

A central and ongoing challenge for Airbnb is the creation and maintenance of trust between its users (Gebbia, 2016). The platform provides different IT artifacts for signaling user reputation, where both hosts and guests can leverage these cues to manage their reputation and to establish trust (Fuller, Serva, and Benamati, 2007; Jøsang, 2007; Bente, Baptist, and Leuschner, 2012; Xie and Zhenxing, 2017). Such means include star ratings (Teubner, Hawlitschek, and Dann, 2017; Zervas, Proserpio, and Byers, 2015), mutual text reviews (Abramova et al., 2015; Bridges and Vásquez, 2018), personal self-descriptions (Tussyadiah, 2016b; Ma et al., 2017), profile images (Teubner et al., 2014; Ert, Fleischer, and Magen, 2016; Fagerstrøm et al., 2017), identity verification and insurances (Teubner and Hawlitschek, 2018) and social connections, displaying how users are connected to others, directly or through mutual friends, usually based on their Facebook contacts (Airbnb, 2011). Importantly, hosts on Airbnb may also inherit the user's general trust in the platform (Han, Koo, and Chung, 2016). In the following, we consider the most widely studied categories of trust and reputation management.

Star Ratings Airbnb's prominent star rating system can be seen as a form of experience assessment. After a completed transaction, guests are prompted to rate their host on a scale of 1 to 5 stars along the sub-dimensions accuracy, communication, cleanliness, location, check in, and value. The resulting average rating score (rounded to the half unit) represents an essential parameter for prospective user interaction. Airbnb displays this cumulative score only for hosts with at least three ratings (Airbnb, 2016b) and more than half of all listings (54.6 per cent) have not reached star rating visibility yet (Ke, 2017b). Moreover, guests are rated by their hosts as well. This assessment comprises an up- or down vote of whether they can recommend the guest to other hosts, a text review and star ratings for cleanliness, communication, and compliance with house rules.

Overall, the distribution of (the hosts') rating scores is subject to a distinct skewness where ratings tend to be on the positive side (see Table A.1). Based on more than 600,000 Airbnb listings worldwide, Zervas, Proserpio, and Byers (2015) report that almost 95 per cent of all listings exhibit an average rating score of 4.5 or 5.0 stars and that hardly any listings have ratings of 3.5 stars or less. Moreover, they find a stronger positive bias in Airbnb reviews than for the same listings when also listed on TripAdvisor. Similar findings are reported by most other studies (Ert, Fleischer, and Magen, 2016; Ke, 2017b). Further, little to no differences in the star rating distribution is found when differentiated by room type (i.e., entire home, private room, shared room). Moreover, comparing Airbnb and Booking.com in five European cities, "a consistent gap of approximately 20 per cent in the average score per city in favor of Airbnb listings" is found (Ert, Fleischer, and Magen, 2016, p. 66). These results echo earlier research on rating systems, showing that over 98 per cent of all exchanged ratings were 5.0 stars (Slee, 2013). Teubner and Glaser (2018) discuss several potential reasons for this skewness and consider survivorship processes where, in fact, low-rated listings exhibit increased churn rates.

Gutt and Kundisch (2016) focus on the rating sub-dimension *value*. They show that—compared to the overall rating—the *value* sub-dimension can offer additional insights for potential guests as it puts a listing's quality in perspective of price. In contrast, Fradkin, Grewal, and Holtz (2018) argue that the high share of positive ratings is not explained by the system itself, but by the high quality standards most hosts meet. This hypothesis is corroborated by two experiments and internal data from Airbnb, indicating that the positivity bias may be caused by:

- Airbnb's efforts of verifying user identities and actively fostering high-quality user profiles;
- Airbnb's explicitly selective ranking algorithm that ranks down unfit hosts (e.g., based on listing quality, location relevance, reviews, host response time and guest and host preferences; Grbovic, 2017); and
- a natural selection process, where low-quality listings receive negative reviews, hence are not booked again, and in consequence drop out of the market.

Interestingly, review scores appear to be subject to spatial influences within a city, where more central areas typically exhibit better scores (Cummins, 2017).

Recently, scholars have begun to use scenario-based choice experiments on the effectiveness of different reputation cues showing, for instance, that the availability of a review score increases a listing's chances of being booked (Ert, Fleischer, and Magen, 2016). In a similar manner, the number of positive reviews is identified as a strong trust-enhancing cue, instrumental for shaping consumers' booking decisions (Abramova, Krasnova, and Tan, 2017). In fact, the effect of star rating availability is supported by:

- results from a trust game experiment among actual Airbnb users; and
- transaction data from the platform itself (Abrahao et al., 2017).

The availability of a high star rating increases others' willingness to trust and it can particularly counter the detrimental trust effects of high social distance.

According to Abramova, Krasnova, and Tan (2017), beyond review score, also the number of reviews represents an important driver for guest's rental decisions. Several studies use this number as a proxy for a listing's popularity and hence its performance (Lee, 2015; Ke, 2017a; Ke, 2017b; Liang et al., 2017). What is frequently reported is that Airbnb listings exhibit a richer-get-richer phenomenon, where "listings with more existing reviews will have more new reviews" (Ke, 2017b, p. 9). Last, listings with Superhost status are found to receive more ratings within a given time frame, and that these are higher on average (Liang et al., 2017).

Text Reviews and Self-Descriptions Beyond star ratings, users on Airbnb rely on text-based elements to build trust. First, users can provide a textual self-description on their profile, that is, provide some personal information such as occupation, hobbies, or life motto (Ma et al., 2017). Airbnb suggests providing a description of at least 50 words highlighting why a user decided to join the "community," their interests, or anything else they believe a prospective interaction partner would want to know (Airbnb, 2017b). Second, along with numerical star ratings, prior transaction partners describe their experiences with each other by means of text reviews. These typically entail statements about the host/guest, travel purpose, and the apartment and its surrounding, representing valuable information for potential future guests/hosts (Bridges and Vásquez, 2018; Bae et al., 2017). The implications emanating from text-based online representation are considerable. Both self-descriptions and text reviews are actively used to reduce perceptions of risk and to prevent users from misunderstanding and unfounded expectations (Jung and Lee, 2017).

Afforded by the availability of textual profile information, recent research has applied text analysis and natural language processing to decipher meaning and implications of such text-based elements and to understand Airbnb's users in greater detail. Tussyadiah (2016b) uses word co-occurrence in the textual self-descriptions to identify and differentiate clusters of hosts. Categories are style of self-presentation, pricing, and activity patterns. Similarly, Ma et al. (2017) find hosts' self-descriptions to refer to different themes (i.e., origin/residence 69 per cent, work/education 60 per cent, interests and tastes 58 per cent, hospitality 53 per cent, travel 48 per cent, relationships 28 per cent, personality 27 per cent, life motto and values 8 per cent) and that a hosts' trustworthiness increases:

- with the length of self-descriptions; and
- or profiles that disclose information particularly referring to work, origin, hospitality, and personal interests.

Text reviews have been subject to in-depth investigations too. Bridges and Vásquez (2018), for instance, explore linguistic patterns in Airbnb reviews, by and large reflecting the high proportion of positive star ratings also in these written evaluations (93 per cent of the analyzed text reviews were classified as positive). Interestingly, 79.5 per cent of all guest reviews mention the host by name (other studies report similar proportions; Alsudais, 2017). Of the 7 per cent not-entirely positive reviews, three out of four came from guests, typically referring to issues with comfort (48 per cent), communication (21 per cent), or cleanliness (15 per cent). The authors suggest that negative experiences are communicated by means of subtle or "lukewarm" cues, for instance by explicitly not writing or emphasizing something.

Importantly, not every user submits a review after each transaction; different sources report review rates between 31 per cent and 72 per cent (Cox, 2019). In this vein, Bae et al. (2017) find that divergence between expectation and trip experience (regardless of whether in a positive or in a negative way) increases the likelihood of review provision. Similarly, the authors show that users perceive reviews as more credible for small social distance between themselves and the host. Review credibility, in turn, supports approval, ultimately resulting in increased booking intentions.

Analyzing word co-occurrence within text reviews, Tussyadiah and Zach (2017) identify five recurrent themes (referring to service, facility, location, feeling welcome, and comfort). Linking these themes to a listing's overall rating, the authors find that the "location" and the "feel welcome" themes are associated with higher ratings, while signal words from the "service" theme are associated with lower ratings. Similarly, Brochado, Troilo, and Shah (2017) distinguish eight themes (stay, host, home, place, location, apartment, room, city). Interestingly, they find that this categorization is robust for different cultures (i.e., India, Portugal, US). Similarly, Camilleri and Neuhofer (2017) identify welcoming, expressing feelings, evaluating location and accommodation, helping and interacting, recommending, and thanking as key components. Similar to the positivity bias in ratings, the positive-to-negative word ratio of 14 million English Airbnb reviews is more than twice as high when compared to a benchmark of Yelp reviews (Ke, 2017b).

Profile Images The intuitive judgement of other people on the basis of their visual appearance represents an innate human behavior. Based on two discrete-choice experiments, Ert, Fleischer, and Magen (2016) show that this intuitive evaluation process leads to a preferred selection of hosts with trustworthy profile images. In a similar manner, Fagerstrøm et al. (2017) find an increased likelihood to rent from hosts with positive or neutral facial expressions. Negative expressions or the absence of images, in contrast, are not even compensated by lower prices or higher ratings, demonstrating the paramount importance of visual, particularly facial cues. Interestingly, women are more affected by facial expressions than men and similarity seeking is found to govern trusting decisions and transactions on Airbnb, where higher social distance (i.e., lower similarity) is associated with lower levels of trust and fewer transactions (Abrahao et al., 2017). Due to the fact that not only hosts but also guests have to market themselves on Airbnb, they are also subject to photo evaluation. Focusing on the decision of hosts to accept or reject booking requests, Karlsson, Kemperman, and Dolnicar (2017) find that women, elderly people, and users with trustworthy photos are more likely to be granted permission to book.

Prices and Pricing

Financial motives represent one of the key factors for buyers on peer-to-peer marketplaces (Bucher, Fieseler, and Lutz, 2016). For many cities such as Berlin, Airbnb listings are roughly 30 per cent less expensive than hotel rooms (BATO, 2016). It is hence not surprising that prices and pricing strategies are of particular relevance for Airbnb which is also reflected in distinct price differences between cities (see Table A.1 and Figure A.1 in the Appendix). Several papers have explored determinants of listing prices, usually based on hedonic pricing models (Rosen, 1974). Such models assume that any valuable amenity (e.g., a whirlpool) or other competitive advantages (e.g., favorable location) will sooner or later be reflected by the price. While this relation is well-established for brick-and-mortar factors in the hospitality and tourism literature (Wang and Nicolau, 2017), the success of Airbnb now begs the question whether these relations transfer to the C2C context and whether additional, soft factors such as a host's reputation and personal branding yield tangible economic value as well. And indeed, based on interviews with hosts, Ikkala and Lampinen (2014) and Ikkala and Lampinen (2015) find that hosts monetize their reputational capital in the form of demanding higher prices.

Several empirical studies have since then supported the notion that higher rating scores, along with other reputational signals (e.g., verified identification, duration of platform membership, Superhost status, number of Facebook friends) in fact translate into price markups (Edelman and Luca, 2014; Abramova, Krasnova, and Tan, 2017; Chen and Xie, 2017; Gibbs et al., 2018a; Liang et al., 2017; Teubner, Hawlitschek, and Dann, 2017; Wang and Nicolau, 2017). For instance, Teubner, Hawlitschek, and Dann (2017) find that an additional star is reflected in a $20 markup for a typical stay at a typical accommodation (2 persons, 2 nights). Moreover, the attainable price is also driven by the host's level of professionalism. Li, Moreno, and Zhang (2015) show that professional hosts:

- generate 16.9 per cent more in daily revenues,
- exhibit 15.5 per cent higher occupancy rates, and
- are less likely to exit the market.

Furthermore, with the Superhost badge, Airbnb provides an own attestation of host superiority (e.g., high response rate, positive evaluations, sufficient number of bookings, few cancelations; Liang et al., 2017). The authors show that guests accept this badge as an indicator of quality and are willing to pay more for a Superhost's accommodation as compared to hosts without the badge. Moreover, the results of Gutt and Herrmann (2015) suggest that pricing is subject to the visual presence of reputational capital, for instance, expressed through the star rating. As outlined above, Airbnb displays the accumulated star rating scores only for listings with three or more ratings. A longitudinal assessment reveals that once a listing surpasses this threshold, hosts monetize their ratings' reputational capital, where "rating visibility causes hosts to increase their prices by an average of €2.69" (Gutt and Herrmann, 2015, p. 7). Similarly, panel data suggests that hosts react to receiving additional reviews, ID verification, and superhost status by increasing prices slightly (i.e., by 0.5 per cent to 1.6 per cent; Neumann and Gutt, 2017).

In contrast to models based on empirical data, choice experiments are used to study the influence of information cues and profile images on user decisions and willingness to pay. Abramova, Krasnova, and Tan (2017), for instance, compare trust-enhancing cues and estimate the marginal willingness-to-pay showing that, for instance, consumers are willing to pay €27.76 extra for a listing with 15 positive reviews. Also, visual information conveyed through profile images has a significant impact on listing prices, as its absence or angry facial expressions are found to be compensated neither by low prices nor high ratings (Fagerstrøm et al., 2017). Ert, Fleischer, and Magen (2016) find that more trustworthy hosts (based on perceptions of their photo) yield higher willingness to pay. Also, they report a significant positive influence of the apartment photos' visual appeal on price, which is consistent with another study's finding that an increase of $2,455 in annual revenues due to high apartment photo quality (Zhang et al., 2016).

Economic Impacts and Media Coverage

Economic Impacts Having established an alternative mode of consumption, it comes as no surprise that Airbnb has affected the "traditional" hotel industry. Arguably, compared to a hotel, a stay at an Airbnb host differs entirely in terms of comfort and overall experience and that hence, Airbnb is not likely to substitute hotels altogether. Recent studies estimate that a 1 per cent increase in Airbnb inventory results in a 0.05 per cent decrease of hotel revenues (Zervas, Proserpio, and Byers, 2017), and that additional Airbnb supply has a negative effect on hotel performance (Xie and Zhenxing, 2017). In contrast, others do not find significant effects of the number of Airbnb listings on hotel sales performance (Blal, Singal, and Templin, 2018). Yet, major hotel and lodging associations consider Airbnb as a threat that is already causing price and revenue cuts—especially during peak times (Ben-Ner and Putterman, 2009). This particularly affects mid-price hotels, for which Airbnb listings are considered a suitable substitute (Guttentag and Smith, 2017).

Beyond the hotel industry, it is suggested that the emergence of Airbnb has also affected local housing markets. While there is currently limited evidence how specifically peer-based accommodation sharing affects prices and availability, there are indications of cyclic dynamics insofar as that rental price increases are highest in areas with already large numbers of Airbnb listings (Schäfer and Braun, 2016), causing further regular apartments to be converted into short-term offers. This consequently puts increasing pressure on the housing market—an effect that has been reported for Boston (Horn and Merante, 2017), Barcelona (Llop, 2017), and Sydney (Gurran and Phibbs, 2017). While for popular neighborhoods in Berlin, a relation between the presence of Airbnb and rental price growth is found (Schäfer and Braun, 2016), none is observed for the city of Hamburg (Brauckmann, 2017). Besides increasing rent levels and the potential effects of gentrification, the increasing frequency of short-term renting raises questions also for those who live in "airbnbified" cities and neighborhoods, including noise, pollution, traffic, nuisance, and waste management (Gurran and Phibbs, 2017).

Media Coverage In view of Airbnb's meteoric success and such impacts on entire industries, cities, and residents, the platform's development was accompanied by ample media coverage and several studies have portrayed this process. Between 2009 and 2013, Airbnb's presence in common mainstream publications passed through three different phases. While first attempts to understand and locate the platform in existing categories turned out to be inappropriate, Airbnb was then described as a distinct phenomenon, and eventually acknowledged as an iconic business model (Mikhalkina and Cabantous, 2015). Similarly, the tech blogging community captured Airbnb's development between 2011 and 2014 as a two-stage process. The first step was to establish a two-sided market with respective network- and lock-in effects and thereafter, a process of augmenting the platform through incremental improvements for consumers and providers followed (Constantiou, Eaton, and Tuunainen, 2016).

Legal and Regulatory Aspects

The character of Airbnb's (and its hosts') business model raises a variety of legal questions and sometimes conflicts with applicable national law. These questions can roughly be structured along the categories housing, taxation, consumer protection, regulation, and liability.

Housing First and foremost, short-term rental is legally restricted in many cities. Consider Berlin as an example. Here, like in most other European capitals, the vacation rental business is flourishing. In 2016, 600,000 guests booked a stay, representing an annual increase of around five percent (Airbnb, 2016c). In the same manner, the number of hosts has grown by around eleven percent. These figures are politically explosive insofar as they suggest that the city's misappropriation act has had little effect (BATO, 2016; Schäfer and Braun, 2016). Since May 2014, hosts are not allowed to rent out entire apartments or houses repeatedly on a short-term basis (with few exceptions). In other European cities, Airbnb's strategy of lobbying and acting upon legislation has been quite successful. For instance, Airbnb agreed on a time limit for renting holiday homes in Amsterdam. Residents are allowed to (fully) rent out their apartments for a maximum of 60 days per year. In London, this limit is 90 days. Here, Airbnb has agreed to block all orders that exceed this number. In other cities with a vibrant tourism industry such as Barcelona, the dispute between Airbnb and municipals is far from being settled (Interian, 2016; Llop, 2017; Gutiérrez et al., 2017; Santolli, 2015).

Taxation Next, there exist concerns with regard to taxation, comprising mainly two aspects. First, many cities charge tourism taxes, typically in the range of 5-10 per cent of the room rate. Private Airbnb hosts usually do not pay this as they are not registered as hotel or tourism operators. In many cities (mainly in the USA), Airbnb was hence forced to cooperate with the fiscal authorities and now transfers the tax directly, a model which is argued for by legal scholars (Lee et al., 2016). Second, rental income is subject to personal taxation. However, the literature suggests that many private hosts ignore the tax relevance of this type of income (Cleveland, 2016).

Consumer Protection and Regulation Another conflict is rooted in the fact that hosts offer products and services that may substitute those of hotels but do not face equally strict regulation, for instance, with regard to hygiene and fire inspection standards (Ben-Ner and Putterman, 2009). This raises questions of consumer protection and competition fairness. In this regard, Airbnb argues that the "self-regulating community" of hosts and guests, supported by the platform's reputation systems, actually can complement, if not replace governmental monitoring and/or regulatory processes (Stabrowski, 2017). Moreover, Airbnb claims to perform background checks on hosts for criminal records and sex offender registries (Airbnb, 2017a; Le Vine and Polak, 2017). As a contrast, Airbnbhell.com offers a platform for guests and hosts to share their negative experiences to raise awareness about its risks and to prevent other people from using it (AirbnbHell, 2019).

The debate on unfair competition between the highly regulated hotel industry and Airbnb revolves around seven key issues which public institutions should consider to prevent pressure on the housing market and to counteract touristification, including taxation schemes, the control of visitor streams, information ownership, safety, consumer protection, fair competition, and the housing market in general (Oskam and Boswijk, 2016). There exists no one-size-fits-all vision for handling short-term rentals in the future. Regulatory measures are intended to protect interests of both visitors and locals and thereby require businesses and hosts to comply. For instance, an analysis of written submissions to the city of Sydney revealed that noise, traffic, parking, and waste, but also a general feeling of unease bothers local residents where short-term rentals penetrate residential areas (Gurran and Phibbs, 2017). Local institutions are required to frame regulation on the basis of individual indicators such as visitor numbers, frequency and type of incidents, collected taxes, and the evolution of housing prices—and it is argued that individual and novel regulation is better suited to govern Airbnb than the existing and one-size-fits-all approaches (Jonas, 2015; Lines, 2015; Oskam and Boswijk, 2016). It is proposed that Airbnb may actively support such efforts by committing to self-regulatory measures such as providing transparency about operated properties and visitors (Quattrone et al., 2016).

Liability Furthermore, questions of liability particularly apply to hosts. First, a guest may (intendedly or not) cause damage to the host's property. For such cases, Airbnb offers a 1-million dollar insurance (Airbnb, 2015a) but it is questioned that adequate coverage can be claimed in case it is actually needed (Lieber, 2014; Dobbins, 2017). Of course, financial compensation will not be able to cover damage or loss of objects of sentimental value. Perhaps even more importantly, liability is largely unclear for cases in which a guest comes to harm, for instance, due to technical deficiencies of the apartment (Booth and Newling, 2016). In particular, Airbnb hosts are considered as landlords (rather than innkeepers) by some jurisdictions in which case they are not held liable for injuries that occur on their property (Loucks, 2015).

Discrimination Last, for peer-based sharing platforms, the general tenet is that more disclosed information leads to better assessments, reduced uncertainty, and hence the facilitation of transactions among strangers. Nevertheless, Airbnb's striving to facilitate the creation of trust may result in further, unexpected consequences. One observation is that African-American hosts are forced to charge lower prices (Edelman and Luca, 2014). A subsequent study demonstrated that also guest profiles with distinctively African-American names are denied 16 per cent more often when requesting a stay than potential guests with distinctively "white" names (Edelman, Luca, and Svirsky, 2017).

Here, rejection rates did not depend on the host's age, experience, location, listing price, or usage (occasional/ professional). Moreover, even the host's own ethnicity did not affect rejection rates, suggesting that in-group thinking or homophily are not at work. In an effort of preemptive obedience, Airbnb prompted its hosts to commit to a non-discrimination statement (Airbnb, 2016b; Benner, 2016). In view of Airbnb's general terms of use, it is argued that users are forced to sign the included arbitration agreements which prevent legal enforcement against cases of racial discrimination and that, further, without regulatory adaptions, such waivers threaten civil rights enforcement (Toto, 2017). Another suggestion is to expand the instant booking option which lets guests book without further host approval (Edelman, Luca, and Svirsky, 2017). As of today, however, only about 25 per cent of all listings offer the instant booking option (see Table A.1). It was also discussed to reduce the prominence of profile photos which do, however, play an unchanged paramount role.

2.1.4 Correlation of Themes, Methods, Foci and Domains

We now analyze the different themes, methods, foci, and domains of the reviewed studies in greater detail. Considering the general occurrence of different themes, the role of profile photos has experienced rather little research attention (9 studies) while user types and their motives to use Airbnb have been subject to much more extensive investigation (45 studies). Moreover, we consider the occurrence of combinations of these factors to derive first insights into possible research gaps. To do so, we use make use of correlation analysis for the outlined measures (see Table 2.2).

A first insight from this pertains to the relations between surveys, empirical work, studies on motives, and the foci on providers/consumers. We see that motives are usually assessed by means of surveys ($r = 0.64$) and hardly by empirical analysis (-0.53). Also, surveys usually focus on consumers (0.67) and hardly on providers (-0.63). In contrast, research on providers is usually based on empirical work (0.46), a method which is, however, underrepresented for the consumer perspective (-0.36). In consequence, research into the providers' motives to adopt and use Airbnb represents a natural opportunity for future work—especially for the domain of tourism as this domain focuses particularly on consumers (0.31). Next, Table 2.2 reveals that studies on legal and regulatory aspects (which tend to be published in law outlets, 0.55) are often conceptual (0.50). Thus, data-driven research may further inform Airbnb-related debates in jurisprudence.

With regard to timely developments, we see that the domain of tourism is taking over recently (0.31), while conceptual work appears to die off (-0.27). Furthermore, we see that empirical work is mainly conducted on pricing strategies and prices (0.37), and in particular so for US/Canada-based samples (0.34).

2.1.5 Discussion and Conclusion

We have taken a look at the research landscape around Airbnb and some fundamental data on the listings supplied through the platform. Airbnb represents a poster child of the platform economy and likewise serves as a guinea pig in a variety of contemporary studies in the domains of Information and Management, Tourism/Travel/Hospitality, Law, and Economics. Along the dimensions of user motivation, trust and reputation, prices, economic and media impacts and legal and regulatory aspects, we provide a structured overview on this timely and emerging field of research. We argue that studying Airbnb represents a highly worthwhile endeavor as the platform represents more than a simple booking portal, but rather a blueprint for an entire category of novel business models—setting *de facto* standards for web design, trust and reputation management, and for the social and behavioral norms of user interaction—also outside the domain of travel and tourism. From this analysis there emerges a set of overarching stylized facts and implications for both research and practice.

Table 2.2: Correlation table of publication properties (n = 118; cut-off |r| <0.25)

			1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
	Year	1																										
Theme	User Motives Types	2																										
Theme	Reputation Systems Trust	3																										
Theme	Text Reviews and Descriptions	4																										
Theme	Photos	5																										
Theme	Prices and Pricing Strategies	6																										
Theme	Economic and Media Impact	7																										
Theme	Regulatory and Legal Aspects	8																										
View	Consumers	9		.50				-.27																				
View	Providers	10		-.46				.26																				
Method	Survey	11		.64				-.25			.67	-.63																
Method	Interview	12		.34																								
Method	Empirical	13		-.53				.37			-.35	.46																
Method	Conceptual	14	-.27							.50																		
Method	Experiment	15																										
Sample	Multi-Sample	16					.26																					
Sample	USA and Canada	17													.34	-.36												
Sample	Worldwide	18																										
Sample	Europe	19																										
Sample	Asia	20																										
Sample	Others	21					.30																					
Domain	Tourism, Hospitality, Travel	22	.31								.31																	
Domain	Information Management	23								-.27																		
Domain	Working Paper	24																		.26								
Domain	Economics	25								.30																		
Domain	Law	26								.55						.56												

Theoretical Implications

First, research on Airbnb with regard to quantity, related fields, used methods, scope, and research questions has experienced tremendous growth over the past years. While earlier work mainly considered user types and motivations, we now see research on reputation mechanisms, user interface design, trust, legal assessments, prices and pricing, geographic aspects, text sentiment, the platform's overall inventory and its impact on established industries. However, not all aspects and methods (and combinations thereof) are equally represented (see Chapter 2.1.4). Future work should hence consider to focus the identified gaps and hitherto scarcely used combinations (e.g., of method and focus).

Second, for platform business models, trust is considered as crucial by scholars, users, and platform providers. A broad variety of mechanisms and artifacts are implemented by the platform and a plethora of studies confirm their effectiveness for creating trust and facilitating transactions. Specifically, positive effects are found for higher star ratings scores (Lee, 2015; Ert, Fleischer, and Magen, 2016; Zhang et al., 2016; Abrahao et al., 2017; Fagerstrøm et al., 2017; Ke, 2017b; Sanchez-Vazquez, Silva, and Santos, 2017; Fradkin, Grewal, and Holtz, 2018), larger numbers of ratings (Li, Moreno, and Zhang, 2015; Zhang et al., 2016; Abrahao et al., 2017; Abramova, Krasnova, and Tan, 2017; Ke, 2017b), the presence of text reviews (Ikkala and Lampinen, 2014; Bae et al., 2017; Sanchez-Vazquez, Silva, and Santos, 2017; Fradkin, Grewal, and Holtz, 2018; Liang, Choi, and Joppe, 2018b; Liang, Choi, and Joppe, 2018a), profile images

(Ert, Fleischer, and Magen, 2016; Fagerstrøm et al., 2017; Karlsson, Kemperman, and Dolnicar, 2017; Liang et al., 2017), personal information (Ikkala and Lampinen, 2014; Ma et al., 2017), and other subordinate factors such as the Superhost badge (Ke, 2017b; Liang et al., 2017), ID verification (Abramova, Krasnova, and Tan, 2017; Jung and Lee, 2017), or favorable room presentation (Zhang et al., 2016; Abramova, Krasnova, and Tan, 2017; Jung and Lee, 2017; Liang et al., 2017). While most of these studies conceptualize trust as an undifferentiated construct, little was it studied in its multi-dimensionality (e.g., ability, benevolence, integrity) or multi-referentiality (e.g., platform, peers) in the context of Airbnb (Hawlitschek, Teubner, and Weinhardt, 2016). As Airbnb, however, deliberately "designs for trust" (Gebbia, 2016), an even more nuanced conceptualization of trust may yield further insights into trust-related entanglements on Airbnb specifically—but also on peer-to-peer platforms in general.

Third, as this literature review has revealed, a large share of work on Airbnb is based on empirical data. For such studies, we observe that the website InsideAirbnb.com is increasingly used as a viable resource, providing data on listings, reviews, and calendars. It appears quite likely that much of the upcoming research will do so too as InsideAirbnb.com, as a data repository, alleviates researchers from the technical burdens of implementing web scrapers and allows for better comparability across results. Research should move toward building atop of a common ground of data structure and vocabulary.

Practical Implications

The present research also yields several managerial implications for the traditional hotel industry. For instance, it becomes evident that managers in the hotel industry can no longer ignore the presence of Airbnb and the type of service it provides to its users (Blal, Singal, and Templin, 2018). Instead, hotels should actively differentiate their offers from Airbnb and emphasize their own strengths. This includes, for instance, strengthening loyalty programs, for which Airbnb does not offer a substitute (Young, Corsun, and Xie, 2017). In addition, hotels can leverage economies of scale to provide access to assets that are hardly being offered by private hosts (open spaces, gastronomic facilities, gyms, etc.) and services (concierge, maintenance) (Akbar and Tracogna, 2018). This is well in line with hotels' higher family friendliness (Mao and Lyu, 2017; Poon and Huang, 2017) and aspects such as instant booking and confirmation, the absence of minimum stay durations, and more reliable room availability throughout the year (Gunter and Önder, 2017). Eventually, with regard to Airbnb, hotels' marketing should particular stress their superiority with regard to process risks, safety, and security (Yang and Ahn, 2016; Mao and Lyu, 2017; Poon and Huang, 2017; Young, Corsun, and Xie, 2017; Malazizi, Alipour, and Olya, 2018).

Another recurrent theme in the literature are motives for using Airbnb and we find that such motives are manifold. Financial (Tussyadiah, 2016a; Guttentag and Smith, 2017; Liang, Choi, and Joppe, 2018b; Liang, Choi, and Joppe, 2018a) and social reasons (Möhlmann, 2015; Tussyadiah, 2015; Guttentag et al., 2018), trust (Tussyadiah, 2015; Mittendorf and Ostermann, 2017; Wang and Nicolau, 2017), and risk-related factors (Lampinen, 2016; Varma et al., 2016; Jung and Lee, 2017) emerge as the most important motives but there are indices of other factors too, including sustainability (Hamari, Sjöklint, and Ukkonen, 2016) and authenticity (Guttentag and Smith, 2017;

Guttentag et al., 2018). Importantly, not only consumers but hosts as well are found to be motivated both by economic and social motives. Interestingly, while most studies identify financial motives as predominant, Airbnb's marketing does not address this direction at all. Apparently, the platform attempts to create an image of a social travelers' community in which money does not play a role at all. Such "sharewashing" practices have recently been discussed as misleading users and the public and it may well be that the disavowal of most users' economic motives harms rather than benefits Airbnb as a company Troncoso (2014) and Hawlitschek, Teubner, and Gimpel (2018). One practical implication standing to reason for Airbnb but also for other platform operators is that they may want to revisit their users' motives, their marketing communication, and possible discrepancies between them.

Limitations

Like any research, the present study is not without limitations. One aspect may concern the literature screening process. Given that there does not exist a natural and clear-cut criterion for what constitutes a sufficiently Airbnb-related paper, this process may be vulnerable to some selection bias. Nevertheless, error sensitivity may be rather low as exclusion criteria were thoroughly discussed among authors. Moreover, given the rapid development of the platform, regulation, and Airbnb-related research, this review must be considered as a snapshot in time. Nevertheless, we are positive that it may help to identify research lacunas.

Future Research

Airbnb's worldwide presence is reflected in a large spectrum of cultural habits, products, and prices—which all interact. Investigating actual Airbnb data reveals that there exist significant differences with regard to market penetration, prices, and more intricate aspects such as reputation scores (see Table A.1 and Figure A.1 in the Appendix). For "local" studies on Airbnb, it is hence important to keep in mind that rash generalizations to other cities and regions, let alone for the entire platform, may not be justified. A striking observation in this regard is the low number of studies that deliberately consider and compare samples of different origins (Brochado, Troilo, and Shah, 2017; Rahimi, Liu, and Andris, 2016). Future research hence should examine socio-demographic, regional, and cultural aspects in greater depth, for instance, with regard to the effect of cultural norms on the roles of user motives, prices, trust building, and reputation (e.g., across Western/Eastern societies).

Moreover, only few studies have set out to conduct experiments on provider-consumer interactions and trust (Abrahao et al., 2017) or actual field experiments directly on the platform (Edelman and Luca, 2014; Edelman, Luca, and Svirsky, 2017). Despite the technical and ethical intricacies of audit studies, this approach represents a highly promising path for future work as it reveals insights into actual, that is, non-hypothetical user behavior. The open data repository InsideAirbnb.com provides monthly panel-like data for an increasing number of cities which open up the possibility of studying dynamic aspects, for instance, with regard to the evolvement of prices, transaction volumes, or user reputation (Teubner and Glaser, 2018). This opportunity should be seized by future work.

Beyond these currently discussed topics, several other, less obvious research gaps come to mind. First, two of the most recent developments include experiences and the platform's automated pricing algorithm (Hill, 2015; Gibbs et al., 2018b). With the introduction of experiences in late 2016, Airbnb attempts to tap into an additional business potential, where locals offer (i.e., sell) guided tours, workshops, and other activities—positioning Airbnb as a wholesale tourism company. Research on such peer-based tourism services is, however, scarce. Moreover, Airbnb's automated pricing tool represents by and large terra incognita.

Second, what is common to many platforms is that users need to market themselves based on their online reputation and/or personal brand (Harris and Rae, 2011; Yannopoulou, 2013; Tussyadiah, 2016b; Dann et al., 2018). With each platform specializing on one particular type of product or service, users handle distinct reputation scores for an increasing number of platforms (Dakhlia, Davila, and Cumbie, 2016). The ever-growing relevance of Airbnb and other peer-based platforms prompts the idea of leveraging one's reputation from one context in other contexts as well, that is, on different platforms. This poses the question of whether (and if so, how) reputation is actually transferable between platforms (Teubner and Flath, 2019). Instead of starting all over again with zero reviews and no reputation, new Airbnb users could refer to their existing ratings on other platforms. This notion of *reputation portability* is identified as an important lever to address issues of platform competition (European Union, 2017, p. 93).

Third, while the rating distribution skewness toward positive ratings on Airbnb is regarded as common knowledge and many studies have described this distribution (Zervas, Proserpio, and Byers, 2015), little is known about the root causes for its occurrence. There exist several conjectures, for instance, on social interactions among hosts and guests, under-reporting of negative experiences, non-anonymity and publicity of reviews, mid- and long-term selection, or strategic reasons in view of future transactions (Dambrine, Jerome, and Ambrose, 2015; Bridges and Vásquez, 2018). Empirical work addressing these suppositions, however, is yet scarce.

2.1.6 Conclusion

Studying Airbnb is due even beyond the questions and issues directly related to the platform as it serves as a template for various other ventures, reflected in many startups' claim to represent "the Airbnb of..." (Horton, Stern, and Zeckhauser, 2016). In addition, many of the mechanisms and design elements used by Airbnb (e.g., star ratings, text reviews, profile images) are being used by most other platforms too. Given the increasing importance of two-sided markets, platform business models, the associated economic, social, and regulatory upheavals, and Airbnb's function as a poster child and role model make it worth studying all the more. In summary, our study provides an overview of work on the accommodation sharing platform Airbnb. The prevalence of personal host-guest interactions—both online and, importantly, also offline—distinguishes the platform from traditional accommodation markets (i.e., hotels) and charges the used IT design elements and mechanisms with particular social and economic meaning. As a highly diverse and steadily growing community of scholars investigates the phenomena surrounding Airbnb, this review can only represent a first step in view of the necessity to sort, structure, and review the vast amount of literature. We hope that researchers and practitioners alike will find this review useful as a reference for future research and as a guide for the development of innovative applications based on the platform's peculiarities and paradigms in e-commerce practice.

Chapter 3

Social and Economic Values on Peer-to-Peer Platforms

3.1 Where the host is part of the deal: Social and economic value in the platform economy

With a general understanding of P2P platforms and the current state of research on their most popular representative, this chapter continues with developing an understanding of why consumers intend to enter a transaction on these platforms. Within an online experimental approach, the following study investigates how providers' appearance on platforms (i.e., their UR) is linked to consumers' intention to enter a transaction with them. The experiment considers three types of UR artifacts: Artifacts that (1) convey personal information (e.g., self- descriptions), (2) are provided by exogenous sources (e.g., star ratings), and (3) conflate both of these informational properties (e.g., text reviews). The results illustrate the dual property of text reviews and that transaction intentions are driven by expected social and economic value to about equal extents.

David Dann, Timm Teubner, Marc T. P. Adam & Christof Weinhardt[1]

3.1.1 Introduction

An ever-growing number of businesses in today's platform economy enable the *renting and sharing* of resources from peer to peer (P2P) (Sundararajan, 2016). One of the predominant applications of these platforms is accommodation sharing.[2] In this domain, platforms such as Airbnb, HomeAway, Homestay, and Wimdu create value by matching potential hosts and guests (i.e., the consumers). To do so, they make use of a variety

[1] This study was published in the *Electronic Commerce Research and Applications* journal, `https://doi.org/10.1016/j.elerap.2019.100923`, (Dann et al., 2020b).

[2] The European Commission quantifies the annual expenditure on P2P platform markets at €27.9bn within the EU and identifies accommodation sharing and renting as one of the key business models (European Commission, 2016). In contrast to B2C e-commerce and P2P platforms such as eBay, real-world social interactions represent an integral part of accommodation sharing. Thereby, it represents a particularly interesting example in view of social facets as the expected personal interactions are substantial.

of user representation (UR) artifacts to create trust between users and hence facilitate transactions (Abrahao et al., 2017; Dann, Teubner, and Weinhardt, 2019).

Listings on accommodation sharing platforms are often run by private individuals, and consumers may hence face significant exposure due to fraudulent offers, unreliability, or inappropriate conditions (AirbnbHell, 2019). Consequently, assessing potential hosts is essential for forming expectations about the economic value one may derive from a transaction. Also, many offers by private individuals are associated with co-usage, also referred to as "on-site hospitality" (Ikkala and Lampinen, 2015, p. 1036), where consumers and hosts share a space at the same time (Teubner, Hawlitschek, and Dann, 2017). On Airbnb, for instance, co-usage accounts for 31.5% of all transactions (Ke, 2017b). Such scenarios imply personal interactions that create an additional social value dimension for consumers. Such value may, for instance, be based on authentic, local, or cultural insights, a personal hospitality experience, or simply pleasant company (e.g., Ikkala and Lampinen, 2015; Lalicic and Weismayer, 2018; Tussyadiah, 2016a). As co-usage is not offered by traditional hotels, accommodation sharing platforms explicitly promote personal aspects (e.g., "Experience a home away from home", Homestay, 2017; "Belong anywhere", Airbnb, 2014a; or "Don't go there. Live there", Airbnb, 2016b).

Anticipating the prospective *offline* experience based on online information renders the realization of transactions highly dependent on hosts' user representation (Ert, Fleischer, and Magen, 2016; Fagerstrøm et al., 2017; Krasnova, Veltri, and Günther, 2012). Overall, this representation (1) may convey personal information (e.g., self-descriptions on occupation, interests, hobbies), (2) may be provided by an exogenous, third party (e.g., star ratings), and (3) conflate both of these properties (e.g., text reviews; Hesse et al., 2020). However, at this stage, there is limited research on how the different UR artifacts affect expected social and/or economic value. We hence pose the following, overarching research question:

RQ: *How do different UR artifacts facilitate co-usage transactions through social and economic value?*

In this paper, we develop a research model tying together different UR artifacts, their informational properties, as well as social and economic value motives. We evaluate our model by means of an online experiment. Participants take the role of consumers who examine prospective hosts' listings. This paper makes three main contributions. First, by causally linking the outlined UR artifacts to booking intentions, we advance the understanding of the driving factors of consumer behavior in accommodation sharing. Specifically, we show that consumers do in fact take prospective *social* value into account. Second, supporting our theoretical reasoning, results show that artifacts providing personal information affect consumers' expectations about social value while artifacts providing exogenous information affect expectations about economic value. Consequently, text reviews emerge as a particularly powerful cue as they conflate both informational properties (personal and exogenous) and also affect booking intentions both through economic and social value expectations. Overall, platform operators should thus be well aware of the different artifacts' nuances and importance as facilitators for transactions. Third, to the best of our knowledge, our study represents the first to examine the dual effect of text reviews on booking intentions through social and economic value expectations. Complementary to previous studies that mainly *describe* the effect of text reviews, our study is one of the first to experimentally test their impact.

3.1.2 Related Work and Theoretical Background

Given the intensity and intimacy of interactions in domains such as accommodation sharing, and how expectations about such interactions ultimately come down to the individual persons, the role of UR artifacts is rendered particularly relevant. In this regard, hosts can leverage expectations about social value to advertise their listing, services, and ultimately themselves (Harris and Rae, 2011; Tussyadiah, 2016b).

Social and Economic Value in P2P Sharing Platforms

While scholars have identified numerous motives for consumers to engage in transactions on sharing platforms (e.g., sustainability-related or anti-capitalistic considerations), economic and social motives have emerged as prevailing (e.g., Hawlitschek, Teubner, and Weinhardt, 2016; Tussyadiah and Park, 2018). Beyond mere economic value, transactions on accommodation sharing platforms inherently include the prospect of social value. As shown in Figure 3.1, in the context of co-usage sharing,

- social value emerges, inter alia, from *authentic and local experiences, new and pleasant encounters, conversation and socializing, or cultural insights,* while
- economic value emerges, inter alia, from *cost savings* (e.g., compared to hotels), *reliability and safety, cleanliness and hygiene, or utility value* (e.g., derived from amenities).

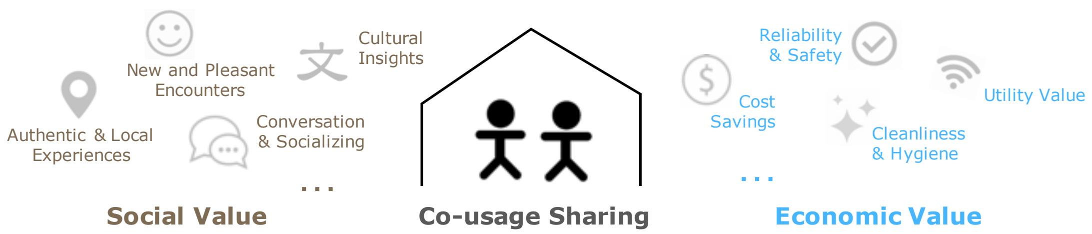

Figure 3.1: Social and economic value in co-usage (accommodation) sharing.

Overall, social value may be defined as "the pleasure, satisfaction, and gratification individuals derive from participating in interpersonal interactions" (Jiang et al., 2013, p. 582). Humans assign value to social factors (Fareri and Delgado, 2014; Sanfey, 2007), and engaging in interpersonal interactions has been a crucial factor in the continuation of the human species (Tamir and Ward, 2015). Consequently, the human brain has developed a variety of processes that reward us when engaging in social activities (Kelley and Berridge, 2002; Tamir and Ward, 2015) and humans seek social value. Krach et al. (2010), for instance, find that some of the most potent stimuli to the human brain are linked to positive social interactions. Also, Fogg (2009, p. 4) argues that "[t]he power of social motivation is likely hardwired in us." Social value can be evoked by a variety of stimuli, including encounters with interesting people of diverse cultural backgrounds (Ikkala and Lampinen, 2015), emotional expression (Rademacher et al., 2010), cooperation and fairness (Lieberman and Eisenberger, 2008), peer approval and friendly gestures (Bhanji and Delgado, 2014), communication (Krach et al., 2010), or simply others' attention (Buss, 1983).

The notion of social value applies to P2P platforms in several ways. Services that create social value are, for example, found to entail higher usefulness for consumers (Barnes and Mattsson, 2017), and the desire to form social ties and community-belonging are some of the driving factors for engaging on P2P platforms (Bucher, Fieseler, and Lutz, 2016; Tussyadiah, 2015). From a consumer's perspective, estimating potential social value relates to various steps throughout transactions with real-world interaction. These include the initial search, sending requests, the transaction itself, and reviewing the transaction afterward. Unsurprisingly, platform operators employ social cues to stimulate expectations about social value (Airbnb, 2014a; Airbnb, 2016b; Homestay, 2017). Thus, a user profile can be seen as a "preview" of the social value that can be expected down the line. It conveys an impression about the chance to meet a person in the real world who may be worthwhile getting to know.

User Representation Artifacts on Sharing Platforms

Platform operators make use of a variety of artifacts for user representation. These artifacts exhibit specific characteristics that can be categorized as (1) providing *personal* information about the host and as (2) providing an *exogenous* view which renders the information particularly credible. A self-description text is an example for the former, while star ratings are an example for the latter. Importantly, there exist artifacts that conflate both properties (e.g., text reviews; see Figure 3.2).

Figure 3.2: Informational properties of different UR artifacts.

Self-descriptions are textual accounts that enable users to create expressive and lively profiles. About 40-50% of Airbnb hosts make use of this option (Ke, 2017b) and express themselves in about 100 to 230 characters to convey a positive self-image by disclosing personal information (e.g., Hesse et al., 2020; Ma et al., 2017; Tussyadiah and Park, 2018). Typical users' self-descriptions refer to their hobbies and interests, occupation, life motto, or why they have joined the platform community (e.g., Tussyadiah, 2016b; Zhang, Gu, and Jahromi, 2019).

Star ratings are a transaction-based numerical aggregation of prior users' experiences (Teubner, Hawlitschek, and Dann, 2017). After a transaction is completed, consumers evaluate their hosts on a scale of 1 to 5 stars, and the (rounded) average rating is displayed on the host's profile. On some platforms, the rating is only displayed if a particular number of evaluations is surpassed (Airbnb, 2016a). Importantly, for the example of Airbnb, slightly *more than half* of all hosts have not crossed this visibility threshold (Ke, 2017b), equipping the availability of a rating score with actual differentiating power (Qiu and Abrahao, 2018). Nevertheless, among hosts that possess a rating score, there is evident skewness in the distribution of ratings towards the maximum value and a standing rating of 4 stars may already appear as rather poor (e.g., Dann, Teubner, and Weinhardt, 2019; Hesse et al., 2020; Ke, 2017b).

Text reviews are descriptions of about 70 to 270 characters that are provided by previous guests (Hesse et al., 2020) and contain valuable information for potential future guests (Veloso et al., 2019). They commonly refer to the overall experience, service quality, the accommodation and its surrounding, and – importantly – personal aspects regarding the host (e.g., Bae et al., 2017; Cheng et al., 2019; Tussyadiah and Zach, 2017). As such, text reviews help consumers to reduce uncertainty and to avoid false expectations (Jung and Lee, 2017). Importantly, not every transaction is concluded with a text review. In fact, a substantial share of listings (35.7%) does not include text reviews (Ke, 2017b). Overall, text reviews conflate both the personal information property (similar to self-descriptions) and represent exogenous information (similar to star ratings).

Research Gap

Previous research has *either* investigated (1) consumers' motives to engage in sharing transactions or (2) the trust-building effects of different UR artifacts (see Appendix B.1). In this study, we conflate these two perspectives, linking UR artifacts to the outlined motives and hence allowing for a more precise attribution of how the availability of specific artifacts affects booking intentions. Moreover, while previous work has *described* text reviews (e.g., Bridges and Vásquez, 2018; Cheng and Jin, 2019; Ke, 2017b), research on their perceptual, intentional, and behavioral effects is scarce. The present study hence addresses a research gap by shedding light on the causal effects of text review availability on consumers' value perceptions and booking intentions.

3.1.3 Hypotheses Development

In our research model, we link consumers' booking intentions to the hosts' UR through the theoretical pathways of economic and social value (see Figure 3.3). While previous research has established the importance of these motives for participating in peer-based sharing *in general*, our study sheds light on how consumers form expectations about economic and social value from a transaction with a *specific* host based on that host's UR. The notion of *economic value* captures aspects such as organizational effort (e.g., issuing booking requests), potential cost savings, as well as associated uncertainty (e.g., potential unacceptable housing conditions). By contrast, the notion of *social value* refers to characteristics of social interactions with the host, including meeting someone who is nice to get to know in person and prospective pleasant socializing (e.g., enjoyable conversations or company). We develop our hypotheses in the following.

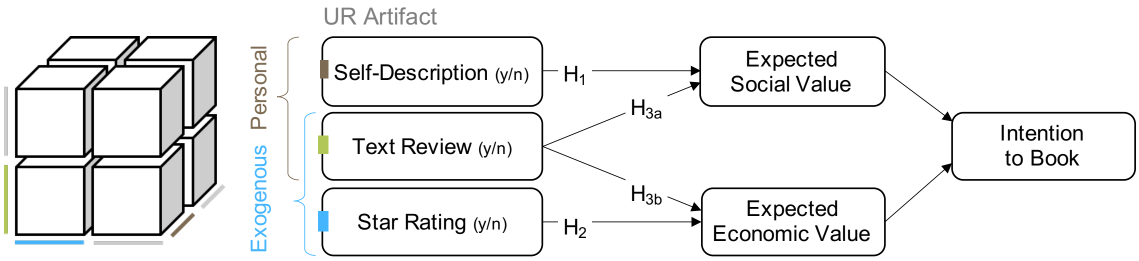

Figure 3.3: Treatment design and conceptual research model.

Influence of Self-Descriptions on Expected Social Value

In their self-description, hosts provide information regarding, for instance, their occupation, hobbies, interests, or activities (Ma et al., 2017; Tussyadiah, 2016b). By deciding how much and what sort of information they disclose, hosts determine their self-presentation and hence, how they are perceived by consumers (Tussyadiah and Park, 2018). An UR artifact that provides personal information contributes to drawing a vivid picture of the particular person and hence allows consumers to perceive them as a real and multifaceted human being. By making use of self-descriptions, hosts can induce feelings of connectedness, sociability, and intimacy – and hence increase liking and understanding (Altman and Taylor, 1973; Janssen, IJsselsteijn, and Westerink, 2014). While there exists a range of different topics that hosts mention in their self-descriptions (Tussyadiah, 2016b), Ma et al. (2017) show that information on occupation, personal background, and personal interests is particularly beneficial. As such, the self-description of a host inherently promotes expectations about the social value of a transaction (Hesse et al., 2020). Consequently, we hypothesize:

H_1 (The Sociability Hypothesis): *The availability of a host self-description has a positive effect on consumers' social value expectations.*

Influence of Star Ratings on Expected Economic Value

Hosts and consumers evaluate each other once a transaction is completed (without knowing the other's evaluation; Fradkin, Grewal, and Holtz, 2018; Hesse et al., 2020). Previous research has established that rating scores represent crucial elements for engendering trust between users of P2P platforms (Chica et al., 2019) and that ratings do in fact reflect the offered good's or service's quality (Gutt and Kundisch, 2016). In particular, star ratings reflect users' aggregated reputation. They typically represent reliable information as they stem from various exogenous sources (e.g., Fagerstrøm et al., 2017; Fagerstrøm et al., 2018; Luca, 2017). We suggest that an (excellent) star rating functions as a positive cue for a host's overall quality and hence increase expectations of economic value. Formally:

H_2 (The Reliability Hypothesis): *The availability of an excellent star rating has a positive effect on consumers' economic value expectations.*

Influence of Text Reviews on Expected Social and Economic Value

Unlike self-descriptions, text reviews are authored by other users, thus stem from an exogenous source. Yet, they can contain personal information about the described host. On Airbnb, close to 80% of all text reviews refer directly to the reviewed host by explicitly naming them (Alsudais, 2017). Similar to star ratings, text reviews represent a track record of consumers' experiences with a certain host. Cui, Lui, and Guo (2012, p. 45) outline that "positive reviews by other consumers are indicative of a product's quality and reputation." For co-usage sharing platforms, text-based evaluations of user experience hence represent an influential cue (e.g., Cheng et al., 2019; Heejeong, 2019; Zhu, Lin, and Cheng, 2019). This applies particularly to hospitality, where consumers prefer (personal) peer assessments over information provided by (professional) travel agencies (Chen, 2008; Gretzel and Yoo, 2008). Apart from the personal information aspects provided by text reviews, they can also reduce consumers' risk perceptions (Liang, Choi, and Joppe, 2018a). Hence, they are likely to play a role also for the formation of expectations on economic value with a particular host (Bae et al., 2017). Yet, not every listing exhibits a text review (Cox, 2019; Ke, 2017b). Consequently, the mere presence of one or more reviews is a potential feature of distinction. In this regard, Abramova, Krasnova, and Tan (2017) find that consumers are willing to pay more for positively reviewed offers. Given this dual role of text reviews, we hypothesize:

H_3 (The Two-Birds-One-Stone Hypothesis): *The availability of a positive text review has positive effects on a) social and b) economic value expectations.*

3.1.4 Research Methodology

To evaluate the proposed model, we conduct a scenario-based online experiment in which participants take the role of prospective consumers on a P2P accommodation sharing platform, considering to book with a specific host. Using experimental treatment manipulation, this allows us to maintain a high level of control over the exogenous variables.

Treatment Design and Stimulus Material

We use a 2 (self-description: yes, no) $\times$ 2 (star rating: yes, no) $\times$ 2 (test review: yes, no) full factorial treatment design. By doing so, we contrast all $2^3 = 8$ possible treatment combinations against each other. Each participant is exposed to exactly one of these conditions (between-subjects design). An exemplary sketch of the host's UR is provided in Figure 3.4.

Self-Description: Participants either see no self-description (50% of all cases) or a brief description of the host. Therefore, we employ four prevalent categories referred to by platform users within their profiles. Following the results of Ma et al. (2017),

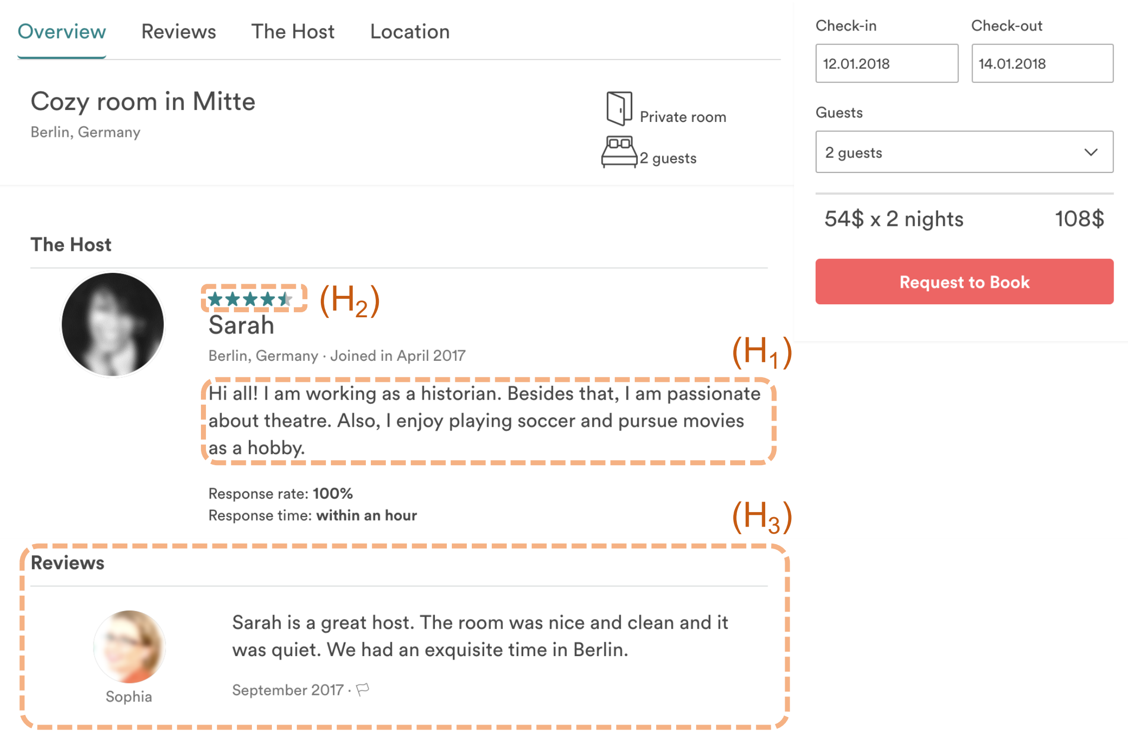

Figure 3.4: Exemplary screenshot of stimulus material with highlighted treatment variables (H_1: self-description, H_2: star rating, H_3: text review).

Tussyadiah (2016b), and Zhang, Yan, and Zhang (2018), our categories encompass the topics occupation, interests, activities, and hobbies. The self-descriptions shown to each participant were randomly compiled from the predefined sets of categories and features shown in Table 3.1.

Table 3.1: Construction set for self-description stimulus.

	Occupation		**Interests**		**Activity**		**Hobby**	
Hi all! I am working	as a physiotherapist.	Besides that I am passionate about	crime fiction.	Also, I enjoy	swimming	and pursue	gardening	as a hobby.
	as a teacher.		biographies.		running		visual design	
	as a medical doctor.		modern history.		bicycling		board games	
	as a historian.		architecture.		playing soccer		modern art	
	in marketing.		photography.		hiking		movies	
	as a biologist.		theatre.		playing volleyball		textile design	

Note: Any of the resulting $6^4 = 1{,}296$ combinations was selected with equal probability.

Star rating: Participants either see no star rating at all (50% of all cases) or one out of the two (positive) rating conditions of 4.5 or 5.0 stars (25% each). In doing so, our treatment design captures the skewed distribution of star ratings on actual P2P platforms such as Airbnb where more than half of the listings (54.6%) have not received a star rating yet and 40.6% either have 4.5 or 5 stars (e.g., Hesse et al., 2020; Ke, 2017b; Zervas, Proserpio, and Byers, 2015).

Text review: Participants either see no text review (50% of all cases) or a positive text review. The structure and tonality of each review is based on actual Airbnb reviews (e.g., Bridges and Vásquez, 2018; Hesse et al., 2020; Ke, 2017b). Specifically, this includes a general statement, a comment on the host, information on the property and its surroundings, as well as a conclusion. For each of these four categories, we randomly select one out of five possible characteristics from the predefined sets shown in Table 3.2.

Table 3.2: Construction set for text review stimulus.

General	**Host**	**House/property/surroundings**	**Conclusion**
Wonderful place to spend a long weekend.	[Name] is a very welcoming host and truly made us feel at home.	The house has everything you could ever really need, and it was simply perfect.	We would definitely recommend this place!
Our stay at [Name]'s home was simply amazing!	[Name] is absolutely lovely and will spare no effort to make you feel welcome.	Really gorgeous location, situated in a beautiful part of town.	Definitely worth booking!
We really loved our stay at [Name]'s house.	Very comfortable place and [Name] gave us some really helpful recommendations and is such a lovely host!	The house is even more beautiful in real life – simply perfect!	By far our favorite Airbnb that we have ever stayed at!
Our stay at [Name]'s house was simply amazing.	[Name] was really welcoming and helpful. [He/she] provided detailed recommendations for us for our weekend and even made us some fresh snacks!	The place was simply gorgeous, and it was perfect to explore the beauty of the city.	We would certainly stay here again!
Amazing experience, couldn't have been better.	A fantastic place to stay. [Name] truly is a very generous and kind host who will spare no effort to make you feel at home.	Beautifully decorated place and a great vibe!	We would stay here again in a heartbeat!

Note: Any of the 54 = 625 combinations was selected with equal probability.

Overall, we seek to display as little information as possible to avoid confounding effects. In particular, this includes the profile images (Karimi and Wang, 2017), for which we use blurred pictures. Host and reviewer names are picked randomly from a set of common first names (see Teubner and Flath, 2019 for a similar approach). As a control variable and to allow for an assessment of the monetary equivalents of the investigated artifacts, one of four prices is displayed ($108, $187, $216, and $374). These values are derived from the price distribution for a typical booking (private room, two nights, including cleaning fee), as reported in prior literature (Teubner, Hawlitschek, and Dann, 2017). Accommodation properties such as amenities, exact location, and cancellation policies are not displayed.

Measures

Whenever possible, we adapted previously validated scales for the context of this study. All items are measured on 7-point Likert scales. In addition to the constructs directly related to the research model, we collect demographic and trait information as control variables, including age, gender, experience with P2P accommodation sharing platforms, and individual risk propensity. All measurement instruments and sources are provided in Appendix B.2.

Procedure and Sample

We recruited subjects from 1) a student subject pool at Karlsruhe Institute of Technology and 2) Prolific.ac. Participants took a median time of 6.42 minutes to complete the experiment and received an average compensation of €12.34 per hour. Overall, 625 participants started the experiment. From these, 486 completed the experiment and passed attention checks (239 male, 247 female). Table 3.3 summarizes the sample characteristics. We determined the required sample size using G*Power 3.1 (Faul et al., 2007). Allowing for a detection of effect sizes d=.20 (alpha=.05) with a power of 1 – beta=.90, the indicated required sample size is 472.

Table 3.3: Sample statistics on demographic control variables.

	Overall (n=486)		**Sub-Sample** Student (n=232)		Prolific (n=254)	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
Female (0: male, 1: female)	.508		.353		.650	
Age (18 – 73)	30.6	10.2	24.7	2.65	36.0	11.4
Risk propensity (0 – 10)	4.85	2.04	5.04	1.94	4.67	2.12
Experience (0: never, 1: at least sometimes)	.529		.647		.421	

Note: SD = standard deviation.

3.1.5 Results

A 2 × 2 × 2 ANOVA reveals significant effects of all treatment variables on booking intention (Table 3.4). Controlling for second- and third-order interactions yields no significant effects. Post-hoc comparisons using the Tukey HSD test confirm significant differences for all three artifacts (all *p*-values < .01). Figure 3.5 and depicts the main effects of the three treatment variable groups on booking intention.

Table 3.4: Main Effects of Self-Descriptions, Text Reviews, and Star Ratings on Consumer's Intention to Book.

Artifact	**ANOVA** F-score	p	**Artifact not displayed** Mean	SD	95% CI	**Artifact displayed** Mean	SD	95% CI
Self-Description	F(1,482) = 8.78	.003	4.14	1.56	[3.85, 4.43]	4.50	1.49	[4.23, 4.77]
Text Review	F(1,482) = 12.7	.001	4.11	1.58	[3.82, 4.40]	4.52	1.51	[4.25, 4.79]
Star Rating	F(1,482) = 9.44	.002	4.02	1.56	[3.74, 4.30]	4.63	1.49	[4.36, 4.90]

Note: SD = standard deviation.

Measurement Model

Next, we evaluate our research model using partial least squares structural equation modeling (PLS-SEM) with SmartPLS 3.0 (Ringle, Wende, and Becker, 2019). We chose PLS-SEM because of (1) its broad scope and flexibility regarding theory and practice (Richter et al., 2016) and (2) its flexibility in handling binary variables (Hair et al., 2016). The sample size satisfies the guidelines by Hair et al. (2016). Power analysis shows that the sample size is adequate to detect small-sized effects with a power of .80 and alpha of .01 (Cohen, 1992).

Table 3.5 summarizes construct descriptives, reliability measures, and correlations. Regarding reliability, all constructs exceed the common thresholds of .70 for Cronbach's

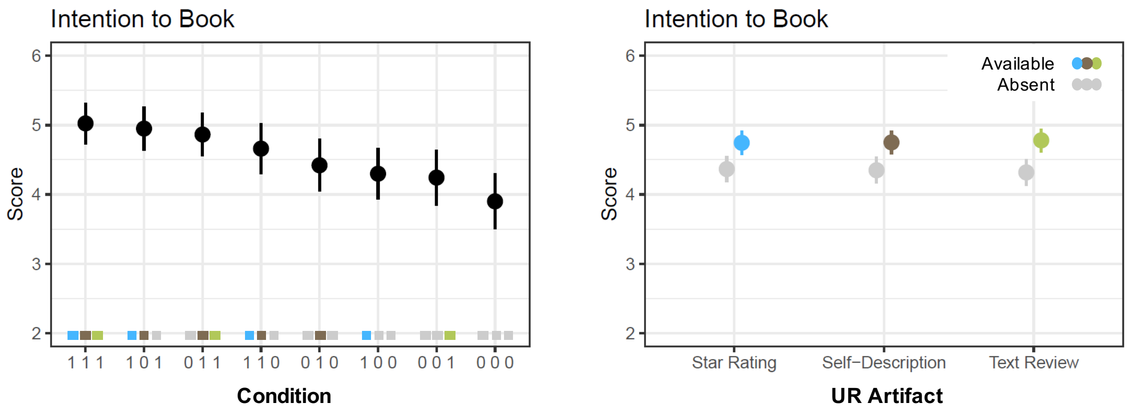

Figure 3.5: Main treatment effects on Intention to Book (ITB), left: by the 2^3=8 treatment conditions (ordered by ITB), right: aggregated by the 3 UR artifacts. Error bars indicate 95% confidence intervals.

Alpha and composite reliability (Bagozzi and Yi, 1988). For convergent validity, all values of Average Variance Extracted (AVE) exceeded the threshold of .50. For discriminant validity, all square roots of AVE were larger than any correlation between that construct and any other construct (Fornell and Larcker, 1981). Further, discriminant validity is verified by the fact that all item loadings on their respective constructs are larger than on other constructs (Gefen, Straub, and Boudreau, 2000) and a heterotrait-monotrait (HTMT) ratio less than the .90 threshold for all constructs (Henseler, Ringle, and Sarstedt, 2015). Item reliability is verified by checking for indicator loadings larger than .70 (Chin, 1998).

Table 3.5: Construct descriptives, reliability measures, and construct correlations (square roots of AVE on the diagonal).

	Descriptives		Composite	Cronbach's	AVE	Q^2	Correlation Matrix		
	Mean	**SD**	**Reliability**	**Alpha**			**ITB**	**ESV**	**EEV**
ITB	4.55	1.63	.923	.876	.800	.408	.895	.618	.604
ESV	4.67	1.20	.893	.821	.737	.071		.858	.429
EEV	3.86	1.67	.962	.947	.863	.303			.929

Note: AVE: Average Variance Explained; SD = Standard Deviation

Structural Model and Hypotheses Testing

We evaluate the model using bias-corrected and accelerated bootstrapping with 5,000 resamples (no sign changes, two-tailed testing). Table 3.6 shows the path coefficients and effect sizes. All hypotheses are supported, explaining 54.6% of the variance in consumers' booking intentions. All UR artifact effects (H_1: self-description, H_2: star rating, $H_{3a/b}$: text review) are fully mediated via expected social or economic value, and the model remains stable in a saturated form (Gefen, Straub, and Rigdon, 2011; Appendix B.3). While the effects between the endogenous survey constructs exhibit medium effect sizes, the exogenous relations between the binary UR artifact variables and survey constructs are rather small. Due to the recent controversy around PLS-SEM, we corroborate our analysis using covariance-based modeling (CB-SEM). This analysis does not reveal any path differences in terms of sign, magnitude, or significance (i.e., all paths remain significant).

Table 3.6: Path coefficients, control variables, and effect sizes.

Hyp.	**Independent Construct**		**Dependent Construct**	**Coef.**	p	**f²**	**Effect Size**
	ESV	→	ITB	.420	.001	.310	Medium
	EEV	→	ITB	.424	.001	.322	Medium
H1	Self-Description	→	ESV	.169	.001	.032	Small
H2	Star Rating	→	EEV	.126	.001	.025	Small
H3a	Text Review	→	ESV	.203	.001	.046	Small
H3b	Text Review	→	EEV	.129	.001	.026	Small
Control variables							
	Participant's age	→	EEV	.122	.002	.020	Small
	Participant's experience	→	ITB	.177	.001	.030	Small
	Participant's risk propensity	→	ESV	.170	.001	.032	Small
	Participant's risk propensity	→	ITB	.086	.004	.016	Small
	Price	→	EEV	-.536	.001	.389	Large
	Price	→	ESV	-.121	.007	.016	Small

Note: ITB: Intention to Book; ESV: Expected Social Value; EEV: Expected Economic Value

Control Variable Analysis

Next, we consider the impact of secondary variables on the model's constructs and relations, including participants' age, gender, experience with P2P accommodation sharing, risk propensity, perceived similarity with the host, and listing price. This control variable analysis yields the following insights. First, higher age is associated with higher expected economic value (β = .122, p = .002). Second, participants' experience (as a P2P accommodation consumer) represents a driver of booking intentions (β = .117, $p <$ .001). Third, higher risk propensity positively affects expected social value (β = .170, p = .001) and booking intention (β = .086, p = .004). Finally, both expected economic and social value are negatively affected by the listing's price (β_{EEV} = -.536, $p <$ .001; β_{ESV} = -.121, p = .007). Table 3.6 summarizes these findings. Importantly, all hypothesized main effects (H_1 to H_3) remain unaffected in terms of magnitude, sign, and significance when adding/removing control variables.

Monetary Equivalents

Based on the four price levels used in the stimulus material ($108, $187, $216, $374), we can now calculate the monetary equivalents of displaying a specific UR artifact. Specifically, when averaging out all other factors, we find that a price increase of $10 yields a decrease in booking intentions of about .03 units on the 1-7 Likert scale. Based on the average differences in booking intentions induced by the three investigated UR artifacts, we can now provide rough estimations of monetary equivalents for self-descriptions (Δ

= .40, \$133), star ratings (Δ = .38, \$126), and text reviews (Δ = .46, \$153). While the exact values must be interpreted with caution, it becomes evident that artifact availability is associated with significant commercial value for hosts.

Multi-Group Analysis

Assessing the reliability of our results, a multi-group analysis (MGA) considering gender, age, risk propensity, and experience with accommodation sharing yields three significant path differences (Table 3.7). First, the positive relation between expected social value and booking intentions is significantly stronger for female than for male participants (Δ = .274). In contrast, the effect of expected economic value on intention to book is larger for male than for female participants (Δ = .196). Moreover, we find that the younger half of participants ascribe more weight to star ratings in view of economic value expectations than the more senior half (Δ = .156). Finally, we did not observe any systematic impact of experience or risk propensity on the relations expressed in the model.

Table 3.7: Multi-group analysis by gender, age, and P2P accommodation sharing experience.

		All		**Gender**				**Age**			
				Male	**Female**			**$<$27**	**$\leq$27**		
		Coef.	p	**n=239**	**n=247**	Δ	p	**n=237**	**n=249**	Δ	p
	ESV $\rightarrow$ ITB	.420	.001	**.301**	**.575**	**.274**	**.999**	.403	.445	.043	.697
	EEV $\rightarrow$ ITB	.424	.001	**.516**	**.320**	**.196**	**.005**	.441	.428	.002	.495
H1	SLFD $\rightarrow$ ESV	.169	.001	.175	.149	.025	.388	.187	.210	.061	.247
H2	STRR $\rightarrow$ EEV	.126	.001	.066	.151	.086	.834	**.208**	**.052**	**.156**	**.038**
H3a	TXTR $\rightarrow$ ESV	.203	.001	.163	.234	.072	.798	.204	.170	.001	.494
H3b	TXTR $\rightarrow$ EEV	.129	.001	.099	.146	.047	.696	.135	.167	.011	.450

Note: *p*-values indicate significance of differences, values above 0.95 also indicate statistical significance.

3.1.6 Discussion and Conclusion

Theoretical Implications

To the best of our knowledge, this is the first study that systematically accounts for consumer perception of different UR artifacts with personal and/or exogenous information, and the social and economic value expectations that arise therefrom. While previous research has either considered general drivers of engaging in sharing transactions (e.g., Barnes and Mattsson, 2017; Hawlitschek, Teubner, and Gimpel, 2018; Lee and Kim, 2018) or tested specific UR artifacts (e.g., Qiu and Abrahao, 2018; Tussyadiah and Park, 2018; Zloteanu et al., 2018), our study conflates both perspectives. We show that booking intentions are affected by social *and* economic value to about equal extents and that these expectations, in turn, depend on the availability of UR artifacts. In comparison to prior research, we find rather large effect sizes for the relations between the social/ economic value motives and booking intentions (Figure 3.6). This *duality* of motives emphasizes that it may not be sufficient to consider one of the motives in isolation while neglecting the other. This extends and partly challenges prior findings, typically reporting a predominant role of economic factors while social motives are frequently found to be insignificant (e.g., Lutz et al., 2018; Oyedele and Simpson, 2018; So, Oh, and Min, 2018) (see also Table B.2 in the Appendix).

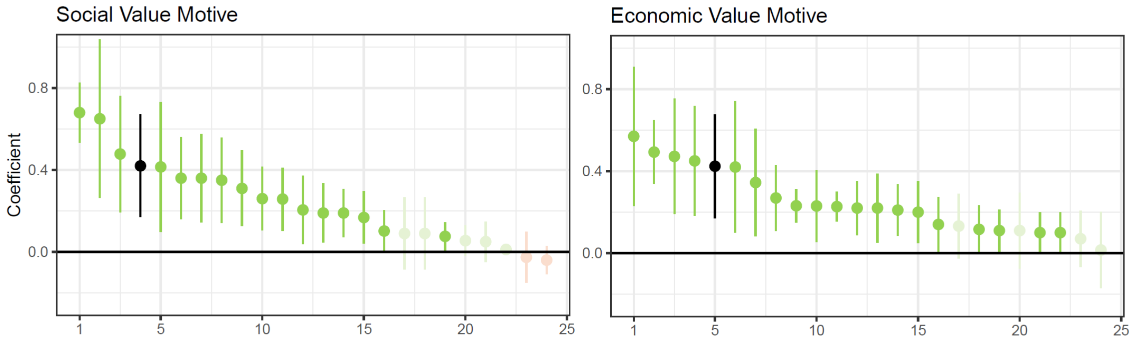

Figure 3.6: Path coefficients of the *social* (left) and *economic* (right) value motives in related work. Studies sorted by path coefficient. Error bars indicate 95% confidence intervals. Positive coefficients in green, negative coefficients in red, non-significant coefficients semi-transparent. Coefficients of our study are indicated in black.
Note: If neither standard errors nor t-values were provided in the publication, we used upper bound approximations based on the information on significance. For some studies, we received this data from the respective study's authors via email, which is gratefully acknowledged.

Several theoretical contributions arise from our study. First, we determine the role of three common UR artifacts within online booking processes and link their informational properties to consumer motives to engage in co-usage sharing. In doing so, we stress the instrumental role of platforms in designing and maintaining (trust-) supporting environments (Kim, Yoon, and Zo, 2015). While self-descriptions serve as a cue for *personal* information and engender expectations about the social value of a transaction (i.e., the *sociability* hypothesis), star ratings provide *exogenous* information that allows to form expectations about economic value (i.e., the *reliability* hypothesis). Importantly, these two artifacts function either via social or economic value exclusively, whereas text reviews conflate both informational properties (personal and exogenous) and, consequently, exert significant effects via both motives (i.e., the *two-birds-one-stone* hypothesis). Noteworthy, emphasizing the importance of this artifact, the individual effects on social and economic value expectations are also strongest for text reviews.

Second, our results expand on previous findings on text reviews from a strictly economic perspective (Abramova, Krasnova, and Tan, 2017), as we also uncover a marked social value dimension. Unlike other UR artifacts in most profiles (e.g., profile pictures), the presence of a positive text review represents an explicit sign of quality. In contrast to product reviews on e-commerce platforms such as Amazon, text reviews on P2P sharing platforms can be assumed to stem from actual transactions.

Naturally, given the personal nature of co-usage accommodation sharing, our findings highlight that the type of transactions needs to be considered carefully. Other modes of P2P sharing exhibit much lower levels of personalness, temporal extent, and physical closeness. Importantly, even accommodation sharing itself needs to be differentiated in this regard. While approximately 30 percent of all hosts offer shared apartments, many others offer entire homes with very limited potential for interaction (Ke, 2017b). In this regard, Tussyadiah (2016b) reports the social motive to be contingent on the co-usage property.

Last, our results provide insights into consumer-specific differences in the weighting of social and economic value. For instance, male participants weight economic value more strongly than social value. This resonates with the tenets of Social Role Theory, suggesting women to have a stronger focus on establishing bonds while interacting with others as compared to men (Kimbrough et al., 2013). Also, we find that the influence of non-personal artifacts (i.e., star ratings) on expected economic value is predominantly driven by younger participants.

Practical Implications

Our study provides practical implications for platform operators and users alike. Against the backdrop that social and economic value exhibit about equal impact on booking intentions, platform operators may want to rethink how to balance their marketing in this regard. Many platforms emphasize the social aspects involved in co-usage so predominantly that basic economic benefits, for instance, compared to hotels, may no longer become evident. Also, female consumers put a stronger emphasis on social value than male consumers, while the reverse pattern can be observed for economic value. Platform operators may build on this and adjust the emphasis on each motive by taking into account consumers' gender.

Furthermore, platforms may consider the potential of matching users based on "social" criteria. This may, for instance, include the ability to search for hosts with specific professions, interests, language skills, or hobbies. Nevertheless, platform operators should be highly aware of potential issues associated with such as social discrimination and harassment (e.g., Dann, Teubner, and Weinhardt, 2019; Edelman and Luca, 2014; Toto, 2017). Hence, promoting social aspects of transactions needs to go hand in hand with (1) communicating and fostering a culture of inclusion and tolerance and (2) an appropriate design of UR artifacts.

Given the power of text reviews, platforms should urge users to follow up on each transaction by writing a review. To support this, the platform may provide building blocks with prefabricated text modules. However, while this may increase the frequency of reviews, it may have unintended side effects such as reduced credibility, repetitive wording and low verbal diversity (Aerts, Smits, and Verlegh, 2017), and hence limited possibilities of expressing acknowledgment, appreciation, critique, or commendation. It may also be an option for platforms to require consumers to write a review before they can issue further booking requests.

Limitations and Future Work

Like any study, the present paper has limitations. First, consumers' actual decisions in P2P accommodation sharing may vary from what they state within a hypothetical scenario. Field experiments should complement our approach (external validity). Despite this, we believe that our stimulus material induces the scenario quite realistically, where structure and visuals are guided by the "look and feel" of popular accommodation sharing platforms. Thereby, we also account for potential influences on the perceived quality of information caused by the mere aesthetics of the presentation (Xu and Schrier, 2019).

Note that our treatment design includes only a selection of all artifacts being used by platforms. While we consider the most common artifacts, other artifacts are of similar interest, for instance, profile images. However, profile images often involve issues of discrimination and effects due to specific photos, thus rendering statements on *general* effects of the artifact less reliable (Edelman, Luca, and Svirsky, 2017; Fagerstrøm et al., 2017).

Furthermore, our design focuses on *positive* text reviews. Bridges and Vásquez (2018) show that consumers communicate less-than-positive experiences by using subtle cues, for instance, by *not* mentioning or saying something. Being able to read between the lines is probably an essential skill for interpreting text reviews. Additionally, the availability of multiple (potentially contradictory) reviews (Maslowska, Malthouse, and Viswanathan, 2017; Park and Kim, 2008) and individual review's helpfulness (Korfiatis, García-Bariocanal, and Sánchez-Alonso, 2012) requires further exploration.

In terms of sample, it needs to be acknowledged that about 47% of the respondents did not have practical experience with P2P accommodation sharing. However, the results of the MGA indicate that whether or not a participant had experience with P2P accommodation sharing did not significantly affect any of the paths in our research model. In other words, the practical implications drawn from our study are not particularly dependent on the differentiation between active versus potential users. Last, we acknowledge that the explained variance of ESV is rather low (10.6%), meaning that there must exist further influences on this variable.

Given the attempt of major platforms to broaden their business beyond accommodation (e.g., guided tours provided by locals; Airbnb, 2016b; Airbnb, 2016a), the notion of social and economic value will undoubtedly remain of interest. Obviously, staying under the same roof for a weekend or longer reaches deep into the involved persons' spheres of privacy (Teubner and Flath, 2019). Examining whether and under which boundary conditions the present findings apply to consumer behavior in other domains represents a natural next step for future research.

3.2 On the dynamics of cognitive and affective trust cues: Behavioral evidence from a two-sided platform experiment

After understanding how UR is connected to users' intentions to enter transactions on P2P platforms, the next chapter focuses on behavior within transactions. Therefore, the following study reports on a laboratory experiment examining the influence of cognitive and affective trust cues within the UR on trusting behavior. Current research widely accepts that the trust-building capacity of trust cues are relatively stable. The experimental study sheds light on the interplay of cognitive and affective trust cues on trusting behavior across multiple transactions. Drawing on the Elaboration Likelihood Model (ELM), the results show that assumptions about stability only applies to cognitive trust cues, associated with the central route of information processing. The effect of the affective trust cues, associated with the peripheral route of information processing, is found to be time-dependent, as their effect on trusting behavior follows an inverted u-shape. The findings indicate that cognitive and affective trust cues are complementary over time.

David Dann, Timm Teubner, Mareike Möhlmann, Florian Hawlitschek & Marc T. P. Adam[3]

3.2.1 Introduction

Peer-to-peer sharing platforms represent one of the most successful and fastest-growing business models in today's e-commerce landscape (Mittendorf, Berente, and Holten, 2019; Sundararajan, 2016; Zimmermann et al., 2018). For example, the accommodation sharing platform Airbnb was only founded in 2008 but reported 2 million daily users by early 2020, being valued at approximately 30 billion USD.[4] Creating and maintaining mechanisms for building trust among users is one of, if not the most crucial endeavor for platform operators (Hawlitschek et al., 2016b; Hawlitschek et al., 2016a; Mittendorf, Berente, and Holten, 2019). Previous research established that peer-to-peer sharing platforms leverage trust between strangers by implementing a range of trust cues, which we define as "information (...) [that] can help build trust" (Nicolaou and McKnight, 2006, p.332). The literature refers to two different types of trust cues—cognitive and affective. First, cognitive trust cues (e.g., Gefen and Straub, 2003; Lee, Lee, and Tan, 2015; McAllister, 1995) facilitate instigating deliberate processes of calculative reasoning. Transaction-based rating scores represent the most widely-employed example for *cognitive trust cues* (e.g., Bolton, Loebbecke, and Ockenfels, 2008; Burtch, Ghose, and Wattal, 2014; Gefen and Pavlou, 2012). Second, *affective trust cues* engender trust through emotions by conveying information that is understood without careful consideration (Komiak and Benbasat, 2006; Stewart and Gosain, 2006). The most

[3]By this thesis's submission date, this study was in the second round of revision at the *Journal of the Association for Information Systems*.

[4]https://www.airbnb.com; https://www.forbes.com/sites/greatspeculations/2018/05/11/as-a-rare-profitable-unicorn-airbnb-appears-to-be-worth-at-least-38-billion/#3e490fd12741

apparent and widely-used example of an affective trust cue in online settings are profile photos (Ert, Fleischer, and Magen, 2016; Riedl et al., 2014). While the general trust-building capacity of both cue types is well-established in the literature, less is known about their dynamic interplay. Especially nascent platforms strongly rely on building trust early on—while at the same time struggling with a need for quick success in reaching a critical mass of transactions (Hodapp, Hawlitschek, and Kramer, 2019). As a result, it is of utmost importance to understand the predictive power of cognitive and affective cues for trust at different stages of platform evolution.

Previous research widely accepts that the effects of trust cues on trust are relatively stable. Once the predictive power of a specific trust cue is (empirically) confirmed, it is assumed to have similar effects on trust across several interactions. To this end, McKnight and colleagues, for instance, have theorized that certain trust cues may indicate stability through structural assurances and situational normality (McKnight, Choudhury, and Kacmar, 2002; Mcknight, Cummings, and Chervany, 1998). Mirroring such assumptions, previous research has shown that the effects of rating scores are relatively stable in the sense that their trust-building capacity is increasing steadily with quality (i.e., better average scores) and quantity (i.e., a larger number of underlying scores) (Cabral and Hortaçsu, 2010).

However, these widely accepted assumptions are challenged by the Elaboration Likelihood Model (ELM) on information processing (Petty and Cacioppo, 1986; Petty, Cacioppo, and Schumann, 1983) once applied to the context of trust research. Petty and colleagues distinguish two different routes of information processing—the central and the peripheral route. The *central route* refers to changes in attitudes resulting from an individual's cognitive considerations of the information's actual quality, such as a careful calculation of advantages and disadvantages (e.g., Bhattacherjee and Sanford, 2006; Chang, Lu, and Lin, 2020; Cyr et al., 2018). Second, the *peripheral route* is not based on extensive contemplation about the issue at hand, but its mode of evaluation relies on affective conclusions drawn from intuitive impulses and impressions (Chang, Lu, and Lin, 2020; Cyr et al., 2018). ELM researchers theorize that changes of attitudes associated with the peripheral route of information processing are temporary (Petty and Cacioppo, 1986; Petty, Cacioppo, and Schumann, 1983), as they are less stable over time (Bhattacherjee and Sanford, 2006). Surprisingly, previous research on trust in sharing transactions has not addressed potential temporary perceptions about affective trust cues processed via the peripheral route yet. These seem to challenge well-established assumptions made about rather stable (McKnight, Choudhury, and Kacmar, 2002; Mcknight, Cummings, and Chervany, 1998) or steadily increasing (Cabral and Hortaçsu, 2010) effects of trust cues on trust as communicated in existing research. In order to explore the varying effect of cues across different stages of platform evolution, we raise the following research question: *How does the interplay of cognitive and affective trust cues affect trusting behavior in sharing transactions over time?*

To address this research question, we conduct a controlled laboratory experiment that allows us to investigate actual trusting behavior over time, that is, across several interactions with different counterparts. Previous research into cognitive and affective trust cues, for instance, on star ratings and reviews (e.g., Abrahao et al., 2017; Banerjee, Bhattacharyya, and Bose, 2017; Cheng et al., 2019) and profile photos (e.g., Ert, Fleischer, and Magen, 2016; Fagerstrøm et al., 2017) has commonly conceptualized trust through self-reported scales on (hypothetical) intentions (Hawlitschek, Notheisen, and Teubner, 2018). While such approaches have undoubtedly informed our understanding of trust in online platform ecosystems, they have neither considered the emergence across several interactions nor how trust materializes in actual rather than intended behavior. To capture actual trust behavior, we hence conduct a controlled laboratory experiment in which participants interact within a peer-to-peer sharing platform environment.

In line with a large body of experimental research (e.g., Blue et al., 2020; Ewing, Sutherland, and Willis, 2019; Gefen, Benbasat, and Pavlou, 2008, we operationalize trust as the amount of money trustors transfer to trustees in an adapted version of Berg et al.'s (1995) trust game. We extend the original trust game to a peer-to-peer sharing platform context with multiple periods and endogenous matchmaking, where participants either take the role of consumers or providers. Specifically, we employ a 2 (star ratings: provided/not provided) $\times$ 2 (profile photos: provided/not provided) between-subjects design. Further, given the focus of our study on peer-to-peer sharing platforms such as Airbnb, our experimental design captures that (1) peer-to-peer matches occur as the result of a free market-based requests-and-response process (endogenous matching), unlike, for instance, on Uber, where the platform determines which driver is matched with which passenger, and (2) exchanges are highly transactional for both sides, unlike, for instance, on eBay, where buyer and seller never meet, and buyers do not face any considerable economic or social exposure. An illustration of this delineation is provided in Appendix C.8.

We contribute to trust research on peer-to-peer sharing platforms in multiple ways. Our starting point is previous Information Systems (IS) research, which widely accepts the effects of trust cues as relatively stable (McKnight, Choudhury, and Kacmar, 2002; Mcknight, Cummings, and Chervany, 1998) or steadily increasing with quality and quantity (Cabral and Hortaçsu, 2010). We apply the ELM's theoretical perspective on this research, challenging this assumption in that it may only apply to cognitive trust cues (associated with the central route) while affective trust cues (associated with the peripheral route) may be temporary, and thus characterized by less stability (Bhattacherjee and Sanford, 2006; Petty and Cacioppo, 1986; Petty, Cacioppo, and Schumann, 1983). To this end, our findings indicate that the trust-building capacity of the affective trust cue of profile photos is rather dynamic and follows an inverted u-shape form. Thus, we contribute to research by deepening the understanding of the interplay of cognitive and affective trust cues as antecedents to trust across several peer-to-peer sharing transactions over time. Our findings demonstrate that affective trust cues associated with the peripheral route may serve as a powerful complement in early stages of platform evolution and may thus help to overcome the inherent "cold start problem" of platforms in general and users thereon in particular (Wessel, Thies, and Benlian, 2017) as profile photos enable a kick-start for trust even before users can establish a transaction-based reputation.

3.2.2 Theoretical Background

Star Ratings as Cognitive Trust Cues

Cognitive trust cues instigate a process of calculative reasoning. Reputation systems are a prime example of artifacts that provide cognitive trust cues (Chen et al., 2015; Mishra, Heide, and Cort, 1998). On peer-to-peer sharing platforms, users tend to interact with transaction partners that they have never met or interacted with before (Teubner, 2018). Thus, users cannot build a history of personal interaction or gain first-hand experience of the other's trustworthiness. Reputation systems help to overcome this gap by enabling access to another user's accumulated digital footprint and documented past behaviors (Bolton, Greiner, and Ockenfels, 2013; Mazzella et al., 2016).[5] This track record, in turn, sets expectations and reduces uncertainty about future behavior, for instance, regarding whether a product or service will be delivered as promised, or about an individual's behavior.

Star ratings are arguably the most widely-used type of reputation system (Abramova, Krasnova, and Tan, 2017; Dann, Teubner, and Weinhardt, 2019) and are employed in some form by most consumer platforms (Hesse et al., 2020; Schoenmüller, Netzer, and Stahl, 2018). Star rating scores are inherently dynamic and evolve over time as they represent the aggregation of feedback from continuous transactions with ever-varying partners (Ba and Pavlou, 2002; Dellarocas, 2006; Rice, 2012). To avoid the risk of collusion or retaliation, these systems commonly follow a simultaneous evaluation process, in which ratings are only revealed after both parties have submitted their evaluations (Fradkin, Grewal, and Holtz, 2018). Consequently, a user's average rating score serves as a quantification of their trustworthiness based on their overall (past) behavior on the platform. Indeed, positive ratings are a driver for demand (Abramova, Krasnova, and Tan, 2017; Ert, Fleischer, and Magen, 2016) and allow users to enforce higher prices (e.g., Gan and Wang, 2017; Gibbs et al., 2018a). Rice (2012) showed that, while the mere existence of a numerical rating system encourages participants to engage in the market at all, the specific information conveyed by the ratings facilitates actual transactions among them. Furthermore, a sufficiently high number of underlying ratings increases the reliability of the rating score as it reduces the potential impact of fraudulent, shill, or erroneous reviews (e.g., Rice, 2012; Tadelis, 2016). Numerical rating systems are hence likely to become more reliable and functional for increasing numbers of completed transactions. Considering the dynamics of peer feedback on eBay, Cabral and Hortaçsu (2010) concluded that star ratings' trust-building capacity depends on factors such as the current rating score's duration, its total number of underlying ratings, as well as the frequency of new ratings. Consequently, accumulating a high number of (positive) evaluations constitutes a potent trust cue to the opposite market side and hence contributes to facilitate transactions.

Profile Photos as Affective Trust Cues

Affective trust cues are processed without careful consideration. Trust as a whole is not solely a calculative process but also involves emotions (Komiak and Benbasat, 2006). Indeed, all social interactions inherently entail the sending and receiving of social cues that allow prospective transaction partners to form trust (Komiak and Benbasat, 2006; Stewart and Gosain, 2006). At the same time, human behavior is subject to emotional,

[5]Pioneered by eBay in the 1990s, reputation systems are primary trust formation tools in digital environments (e.g., Gefen and Pavlou, 2012; Rice, 2012) and have been widely adopted on peer-to-peer sharing platforms (Hesse et al., 2020). On peer-to-peer platforms, users can commonly only submit a rating and/or a review after a completed transaction.

spontaneous, and impulsive traits, rendering affective trust cues pivotal for trust formation on peer-to-peer sharing platforms. Due to the human brain's ability to intuitively process human faces, profile photos are one of the most common affective trust cues in online settings (Kanwisher, McDermott, and Chun, 1997). In this regard, neuroscientists identified the fusiform face area in the extrastriate cortex as being "selectively involved in the perception of faces" (Kanwisher, McDermott, and Chun, 1997, p. 4302). This general innate face orientation appears to be genetically coded into humans (Anzellotti and Caramazza, 2014), as infants react to face patterns within the first minutes after birth (Goren, Sarty, and Wu, 1975), and the process of detecting facial expressions is an unconscious process in the magnitude of milliseconds (Willis and Todorov, 2006).

By disclosing a personal profile photo, users may provide clues regarding their gender, ethnicity, approximate age, or lifestyle, that is to say, their social identity. Like other social cues, human faces can foster trust (Cyr et al., 2018; Gefen, Karahanna, and Straub, 2003; Gefen and Straub, 2004; Hassanein and Head, 2007; Ou, Pavlou, and Davison, 2014). Specifically, the use and effects of photos within online profiles represent a strong trust-building cue that can enable e-commerce transactions (Qiu and Benbasat, 2010; Steinbrück et al., 2002) and positively affects trusting behavior (Ert, Fleischer, and Magen, 2016; Fagerstrøm et al., 2017). Steinbrück et al. (2002), for instance, showed that embedding user photos on an e-vendor webpage's positively influences consumer perceptions about the e-vendor's trustworthiness. Similarly, Teubner et al. (2013) showed in a laboratory experiment that photos foster resource sharing in gift-giving networks.

It is not surprising that most platforms offer customizable profiles, and the majority (if not all) users make use of profile photos (Ert, Fleischer, and Magen, 2016; Fagerstrøm et al., 2017; Hesse et al., 2020; Teubner et al., 2014). In fact, many platform operators actively encourage their users to upload a profile photo when setting up their account. The ride sharing platform BlaBlaCar even provides a search option allowing users to filter rides based on the condition that the driver has uploaded a profile photo (BlaBlaCar, 2018) and states that on average, users with a profile photo are contacted three times more often than those without a profile photo.

Experimental Studies

However, only few *experimental* studies have considered the effect of cognitive and affective trust cues on trusting behavior—typically operationalized by variations of the seminal trust game (e.g., Bente et al., 2014b; Qiu and Abrahao, 2018). Furthermore, our literature review (Table 3.8) reveals certain limitations of previous research, as it (1) either captures affective or cognitive cues, but not their interplay (e.g., Ewing, Sutherland, and Willis, 2019; Kas, Corten, and Rijt, 2020), (2) only considers one side of the trust game without allowing for actual two-way interactions (e.g., Dai et al., 2018), (3) comprises only one single period of transactions (e.g., Barbosa et al., 2020; Qiu and Abrahao, 2018), or (4) matches transaction partners exogenously instead of endogenously (e.g., Bolton, Katok, and Ockenfels, 2004a; Ignat, Dang, and Shalin, 2019).

Table 3.8: Related literature (behavioral experiments, incentivized); * = feigned trust game

Source	Experimental Design			Trust Cue					Trust Cue Type(s)		Sample	
	Matching	#Periods	Setup	Photo	Avatar	Rating	#Ratings	History	Text	Affect.	Cogn.	Size	Origin
Bolton, Katok, and Ockenfels (2004a)	exogenous	30	Lab					×			×	144	US
Charness and Gneezy (2008)	exogenous	1	Lab						×		×	n/a	US
Bolton, Loebbecke, and Ockenfels (2008)	exogenous	15	Lab					×			×	216	n/a
Ben-Ner and Putterman (2009)	exogenous	7	Lab						×		×	194	US
Bente, Baptist, and Leuschner (2012)	none*	9	Lab	×		×				×	×	36	Germany
Ho (2012)	exogenous	10	Lab						×		×	58	US
Rezlescu et al. (2012)	none*	40/70/20	Online		×			×		×	×	87	n/a
Rice (2012)	exogenous	stochastic	Lab			×					×	90	n/a
Bolton, Greiner, and Ockenfels (2013)	by bidding	60	Lab			×	×				×	192	German
Bente et al. (2014a)	none*	12	Lab		×	×				×	×	88	Arab/German
Bente et al. (2014b)	none*	9	Online		×	×				×	×	126	German
Riedl et al. (2014)	none*	10	Lab	×	×					×		18	German
Teubner et al. (2014)	endogenous	15	Lab	×	×					×		216	German
Ananthakrishnan, Li, and Smith (2015)	none*	1	Online						×		×	109	US
Ewing et al. (2015)	none*	5	Lab	×				×		×	×	72	UK
Hawlitschek et al. (2016a)	exogenous	1	Lab							×		92	German
Qiu and Abrahao (2018)	none*	1	Online			×	×				×	5,277	US
Dai et al. (2018)	none*	16	Lab	×		×				×	×	40	US
Ewing, Sutherland, and Willis (2019)	none*	5	Lab	×						×		143	UK
Ignat, Dang, and Shalin (2019)	exogenous	25	Lab			×					×	30	n/a
Barbosa et al. (2020)	none*	1	Online		×	×						4,499	US/Canadian
Blue et al. (2020)	exogenous	16	Lab	×		×			×	×	×	27/61/29	Chinese
Kas, Corten, and Rijt (2020)	exogenous	18	Lab					×			×	228	Dutch
Keser and Späth (2020)	exogenous	20	Lab			×	×				×	300	German
This study	endogenous	6	Lab	×		×	×			×	×	144	European

Elaboration Likelihood Model

The ELM, introduced by Petty and Cacioppo (1981), is a general theory of attitude change that provides a framework for understanding persuasive communication. The model describes the processing of informational stimuli through two routes, the *central* and the *peripheral* route. Information that is processed via the central route is mainly evaluated with regard to aspects that involve more thorough cognitive processing, including the actual underlying arguments, quality, and the potential resulting merits. The influence of information processed via the central route on attitude changes is considered to be persistent and resistant, rendering the central route decisive in its influence on trust-building. In contrast, information that is processed via the peripheral route is evaluated affectively and heuristically. Attractions, impulses, and triggers become dominant factors. Those include, for instance, the visual appeal of the provided information or the presumed competence of the person associated with it (Chang, Yu, and Lu, 2015). Peripherally processed information is considered to be rather weak and unsustainable in its influence on attitude change. However, even though information processed via the central route is considered to be more influential (Chang, Lu, and Lin, 2020; Petty, Barden, J., 2009), information processed via the peripheral route also affects consumer behavior (Chen, Kim, and Lin, 2015; Greiner and Wang, 2010).

Emerging from social psychology, ELM found several applications in marketing-related domains (e.g., Chang and Thorson, 2004; Kim, Kim, and Park, 2010). IS literature considered ELM for the evaluation of expert systems (Dijkstra, 1999; Mak, Schmitt, and Lyytinen, 1997), online shopping (Chang, Lu, and Lin, 2020; Zhou, Lu, and Wang, 2016), privacy concerns (Angst and Agarwal, 2009), technology acceptance (Bhattacherjee and Sanford, 2006; Li, 2013), and web personalization (Ho and Bodoff, 2014; Tam and Ho, 2006). ELM is particularly well-suited to study the effects of trust cues because it is able to differentiate the influence of different cue types on attitude change and behavior. In contrast to other theoretical models, such as Mcknight, Cummings, and Chervany (1998) or Signaling Theory (Spence, 1973), ELM is not limited to static trust relationships at a fixed point in time but provides a theoretical framework to understand dynamic effects of these trust cues. Building on ELM, we can identify cognitive and affective trust cues to information that is processed via the central or the peripheral route. We provide definitions of relevant terms in Table 3.9.

Table 3.9: Definitions of relevant terms

Term	Definition
Trust Cue	Information that helps to build trust in another person.
Cognitive Trust Cue	Trust information that is processed involving some degree of calculative reasoning (e.g., star ratings). According to ELM, cognitive trust cues are processed via the central route.
Affective Trust Cue	Trust information that is processed affectively and, most likely, without careful consideration (e.g., profile photos). According to ELM, affective trust cues are processed via the peripheral route.
Central Route	Mode of evaluation relies on thorough consideration and cognitive evaluation of the information's actual quality. Resulting attitude change is stable.
Peripheral Route	Mode of evaluation relies on affective conclusions drawn from intuitive impulses and impressions. Resulting attitude change is instable.

First, the persuasiveness of information processed via the central route inevitably hinges on the reliability-determining quality of the information itself (Bhattacherjee and

Sanford, 2006; Li, 2013; Zhou, Lu, and Wang, 2016). In turn, this quality is directly dependent on the information's completeness and accuracy (Chang, Lu, and Lin, 2020). Cognitive trust cues, such as star ratings, fulfill all typical characteristics of centrally processed information. They require a certain amount of deliberation on the assessment of the actual argument quality, and their persuasiveness gains in completeness and accuracy as the number of underlying transactions increases. For instance, a star rating of 5 (out of 5) stars from one single assessment is undoubtedly less complete, accurate, and reliable than an average star rating score of 4.5 stemming from ten assessments. Within the tenets of ELM, star ratings as a cognitive trust cue should be processed via the central route.

Second, information typically processed through the peripheral route relates to "non-informational aspects" (Alpert, Alpert, and Maltz, 2005) such as meta-information and less to actual argument quality (Bhattacherjee and Sanford, 2006). Meta-information includes, for instance, the mere aesthetics of how the information is presented (Chang, Yu, and Lu, 2015) or triggers of simple affective states (Alpert, Alpert, and Maltz, 2005). Affective trust cues, such as profile photos, fulfill the typical characteristics of peripherally processed information. Commonly, they provide additional (meta)-information, which can be processed without thoughtful consideration (e.g., background information on the associated person). Besides, they can contribute to the information's visual appeal and affective impact—for instance, by being perceived as vivid and aesthetic (Cyr et al., 2009; Hassanein and Head, 2007). Thereby, the ELM suggests that profile photos as affective trust cues should be processed via the peripheral route.

3.2.3 Hypotheses Development

The Influence of Star Ratings on Trusting Behavior (H_{1a}, H_{1b})

Star rating systems are widely-used to establish trust across various contexts (Dellarocas, 2003). Building on the ELM, we argue that star ratings contribute to building trust as cognitive cues via the central route. While the general effectiveness of star ratings is well-established, the theoretical lens of ELM allows to investigate their influence over time (Kitchen et al., 2014). In this sense, star ratings represent a type of persuasive message that is of high personal relevance for a decision-maker in a peer-to-peer sharing context. In absence of strong distractions, processing a message's content via the central route of persuasion is likely and will lead to behavioral change—in this case, in trusting behavior (Petty and Cacioppo, 1986). Extant literature suggests that a cue's strength impacts persuasion outcomes (e.g., trust; Kim and Benbasat, 2009). Updating a star rating periodically (through additional transactions) not only improves it continuously in terms of reliability by reducing the potential impact of fraudulent, shill, or erroneous reviews (e.g., Rice, 2012; Tadelis, 2016) but also in terms of completeness and accuracy. Thus, we expect that the influence of continuously updated star ratings will result in an increasing effect on trusting behavior over time. In line with previous research, we expect the increasing effect to be stable over time since attitudes that result from central route processing tend to be marked and persistent (Bhattacherjee and Sanford, 2006; Petty, Barden, J., 2009).

H_{1a}: *The availability of star ratings as a cognitive trust cue has a positive effect on trusting behavior in peer-to-peer sharing transactions.*
H_{1b}: *The effect of star ratings on trusting behavior in peer-to-peer sharing transactions increases over time.*

The Influence of Profile Photos on Trusting Behavior (H_{2a}, H_{2b})

The effects of human images and profile photos on trust have been confirmed in various contextual settings, including many sharing economy platforms (Cyr et al., 2009; Ert, Fleischer, and Magen, 2016). Within IS literature, the positive effect of profile photos on trust is commonly explained by Social Presence Theory, that is, the idea that specific forms of interaction require a "fitting" medium that allows the provision of necessary information, such as the extent of users being psychologically present (Cyr et al., 2009). More recent studies link the concept of perceived social presence to ELM (Cyr et al., 2018). The central argument in conflating Social Presence Theory with ELM is that human photos can induce perceptions of "exuding warmth," which, in turn, cause increased issue involvement (i.e., an individual's motivation) in processing via the peripheral route and thus result in attitude changes. In the context of their experimental setup, however, Cyr et al. (2018), somewhat surprisingly, find no empirical evidence for the effect of perceived social presence on issue involvement. The authors argued that the specific context was not suited to induce feelings of warmth and sociability and, thus, recommend to investigate the positive effect of social presence conveyed through photos through the lens of ELM in further contexts.

As the context of peer-to-peer sharing puts a particular focus on the perception of profile photos, we argue that the processing of these affective cues will—other than in the study setup of Cyr et al. (2018)—lead to an effect on trusting behavior. We expect that the profile photos will be processed as affective trust cues through the peripheral route, yielding a peripheral attitude change and, thereby, increase trusting behavior. Since profile photos convey no persuasive argument per se, they rather trigger "relatively primitive affective states" (Petty and Cacioppo, 1986, p.134) such as the perception of social presence. The triggered state becomes associated with the subjects' attitude and thus results in a positive effect on trusting behavior. However, we expect the effect to decrease over time for mainly two reasons. First, attitudes formed through the peripheral route tend to be "weak" and prone to decay over time (Bhattacherjee and Sanford, 2006; Petty, Barden, J., 2009). Since—in contrast to star ratings—the informational value of profile photos does not change over time, their impact can be expected to decay. Second, attitudes that are formed via the peripheral route are less resistant to counterarguments (Petty and Cacioppo, 1986). A strong counterargument to a weak positive attitude towards trusting behavior is the actual experience of exploitation (i.e., untrustworthy behavior). While, in general, negative experiences are rare on established peer-to-peer sharing platforms (Zervas, Proserpio, and Byers, 2015), the likelihood of exposure increases with the overall number of transactions over time. The low resistance of the positive attitude formed through the mere peripheral processing of profile photos will thus result in a decreasing effect on trusting behavior over time.

H_{2a}: *The availability of profile photos as an affective trust cue has a positive effect on trusting behavior in peer-to-peer sharing transactions.*
H_{2b}: *The effect of profile photos on trusting behavior in peer-to-peer sharing transactions decreases over time.*

3.2.4 Method

To investigate the outlined research question, we conduct a controlled laboratory experiment. Behavioral experiments for investigating platform-related questions have experienced increasing popularity in various fields. Most importantly, the use of experiments enables causal inferences, augmenting the inferential power of correlative models, and thus bearing the potential to enrich existing research (Friedman and Cassar, 2004).

Treatment Structure

Participants engaged in a series of peer-to-peer sharing transactions in a proprietary web interface reflecting typical features of "Airbnb-like" platforms. Thereby, each participant either took the consumer or the provider role, and kept this role for the entire experiment. The experiment had a 2 (star ratings: yes/no) $\times$ 2 (profile photos: yes/no) full factorial between-subjects design. Further, to capture the dynamics of cognitive and affective trust cues over time, each experimental session included a total of 6 periods. To avoid end-game effects, some vagueness was introduced in that participants only knew that the experiment would have between 5 and 8 periods (Bolton, Greiner, and Ockenfels, 2013; Rice, 2012).

Based on the two-by-two design, Figure 3.7 shows examples of how the user profiles were displayed in the four treatment conditions. Thereby, it is important to note that all participants in a given experimental session were allocated to the same treatment condition. Specifically, each experimental session included 12 participants, who were randomly allocated the roles of consumers and providers (6 each). Hence, depending on the treatment condition, either all 12 participants in this cohort were able to see and provide star ratings, or none of the participants were. Similarly, either all 12 participants were able to see profile photos, or none of them were. In total, we conducted three sessions for every treatment condition, resulting in a total sample size of 144 participants (= 4 conditions $\times$ 3 sessions $\times$ 12 participants). This sample is sufficient to detect effects of size .25 with a power of $1-\beta$=.917 (4 treatment groups; 6 periods; α=.05; Faul et al., 2007).

Star ratings—In the star ratings conditions, consumers (providers) saw the providers' (consumers') average rating scores (rounded to the half unit) along with the number of ratings received. In addition, each participant also saw their own average rating score. Participants evaluated each other on a scale from 1 to 5 stars after they had completed a transaction. To avoid retaliation or tit-for-tat strategies (or the anticipation thereof), ratings were submitted *simultaneously* (i.e., without knowing the rating one receives from one's transaction partner). In contrast, in the conditions without star ratings, participants could neither see any other participants' ratings nor did they rate each other after the transactions.

Profile photos—In the profile photos conditions, participants' user profiles included a photo as provided by the participants. A few days prior to the experiment, the research

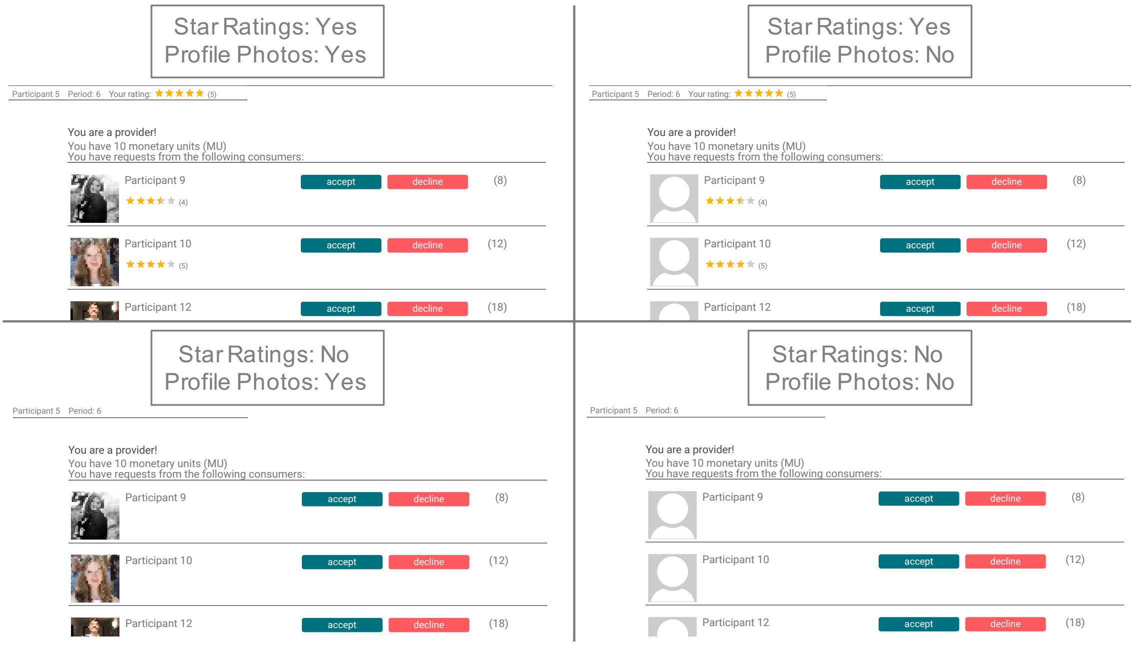

Figure 3.7: Examples for the display of user profiles in the four different treatment conditions

Note: The examples are from the provider perspective. The corresponding screens for the consumer perspective are shown in Appendix C.6 (Figures C.8-C.17). Profile photos are pixelated to preserve participants' privacy.

team contacted participants via email to advise that in the experiment, they would engage with others through an online platform. In that email, participants in the profile photo conditions were additionally informed that they may represent themselves to other participants by means of a profile photo, which they were able to provide via return email before the experiment. They were advised that the photo should ideally have a height-width ratio of roughly 4:3 with sufficient resolution. No other instructions were provided with regard to the photo's content or style. All 72 participants in the profile photo condition provided a profile photo. Within these photos, the participants' face was clearly visible in 60 cases, partly visible in 5 cases, and not visible in 7 cases.[6] In the conditions without profile photos, participants were not able to provide a photo and instead were all represented by a uniform default image (see Figure 3.7; right-hand side).

Experimental Task

In order to operationalize and assess trusting behavior, we build on Berg et al.'s (1995) seminal trust game, following the design of Hawlitschek et al. (2016b). First published in 1995, the trust game has become one of the most commonly applied experimental tasks for modeling a large variety of real-world transactions (Riegelsberger, Sasse, and McCarthy, 2005). In the IS domain, it has been applied to study a variety of artifacts such as avatars (Riedl et al., 2014), fraudulent reviews (Ananthakrishnan, Li, and Smith, 2015), ratings (Bolton, Katok, and Ockenfels, 2004a; Rice, 2012), and user interface

[6]Complementary analysis showed that the degree of face visibility within the profile photos did not yield significant differences in behavior (see Appendix C.2).

design in general (Hawlitschek et al., 2016a).

In the original trust game, two subjects—the trustor and the trustee—engage in two stages. In the first stage, the trustor decides on how much of an initial endowment (e.g., $10) to transfer to the trustee. The transferred amount y is multiplied by a factor greater than one (e.g., by 3). In the second stage, the trustee then decides on how much of the received (multiplied) amount to return to the trustor (z). These transferred amounts are generally considered as manifestations of *trusting behavior* (y) and *trustworthiness* (z). Building on the transactions on actual peer-to-peer sharing platforms, we refer to the trust game's player types as providers (i.e., the trustors) and consumers (i.e., the trustees). The basic interaction of the trust game is thus a simplified analogy to the interactions on Airbnb-like peer-to-peer sharing platforms, where providers entrust a private resource (e.g., their apartment) to consumers, who will use and return it either in a trustworthy (e.g., clean and intact) or in an untrustworthy (e.g., dirty and/or marred) manner.

Further, to model peer-to-peer sharing transactions, we extend Berg et al.'s (1995) experiment by (1) a matching phase in which participants are able to form dyads themselves, and (2) a booking fee that creates exposure also for consumers when entering a transaction. These two extensions refer to the actual booking process on Airbnb-like platforms, where selecting and booking a resource in advance (only based on the available information revealed through the platform) exposes consumers to the risk of paying for a resource that could potentially fail to meet their expectations. Taken together, the experimental task comprised three phases: (I) matching, (II) transaction, and (III) rating, as summarized in Figure 3.8. These three phases resemble the basic mechanics of sharing platforms such as Airbnb, BlaBlaCar, or Drivy, on which consumers first request a resource (apartment, spare seat, car) from a provider and wait for confirmation. Second, after the provider has accepted the request, consumer and provider enter the transaction, where the provider grants access to their private resource in exchange for a payment. Third, provider and consumer mutually rate each other based on their transaction experience.

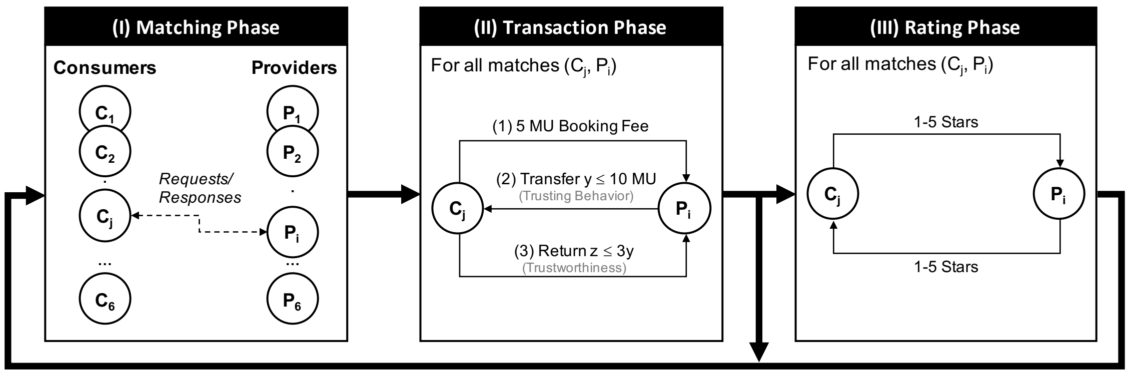

Figure 3.8: The three phases of the experimental task
Note: As per the treatment structure, each participant engaged in six periods of the experimental task. The rating phase only applies in the star rating condition.

(I) Matching Phase—To capture the notion that peer-to-peer sharing transactions are commonly initiated by consumers and confirmed by providers, our experimental task includes a matching phase in which groups of participants form dyads themselves (Bolton, Katok, and Ockenfels, 2004a). Note that any consumer-provider dyad usually only occurs very few times within peer-to-peer sharing (or even only once; Teubner, 2018). To account for this fact, consumer requests were restricted to providers that they had not engaged within the preceding two periods.[7][8]

- Consumers could send one request at a time. If the provider declined the request, the consumer was able to submit a request to one of the remaining providers (if any). Importantly, in each period, consumers could also abstain from sending requests at all and instead click "skip period."

- Providers could receive multiple requests from different consumers, but only accept one request in any given period. Once a request was sent, the provider saw the requesting consumer's profile along with buttons to either accept or decline the request (Figure 3.7). If the provider did not respond within 30 seconds, the request was automatically withdrawn. Once a provider accepted a request, all contingent requests from other consumers were automatically declined. Similar to consumers, providers were able to skip the current period and decline all incoming requests.

The matching phase ended when (1) all existing requests had either been accepted or declined, and (2) no further requests were possible (e.g., because consumers/providers without matches decided to skip the period).

(II) Transaction Phase—Once a provider confirms a consumer's request, the corresponding consumer-provider dyad enters the transaction phase. This phase includes three steps. In the first step, the consumer pays a booking fee of 5 MU to the provider. This reflects the fact that the consumer also faces some risk in that the provider may not "deliver," that is, for the case of accommodation sharing, provides an apartment in bad or unacceptable condition. In the experiment, this may occur when the provider decides not to transfer any MUs, which would leave the consumer with a loss compared to not engaging in a transaction at all. In this second step, the provider decides on how much of their endowment to transfer to the consumer (y) where $0 \leq y \leq 10$ MU. Hence, the providers' endowment of 10 MU represents the private asset (e.g., their apartment) that they bring into the transaction. The transferred amount y (trusting behavior) is tripled and credited to the consumer. Contextualized to the setting of peer-to-peer sharing platforms, this transfer captures the service delivery from the provider to the consumer. In the third step, the consumer decides on how much z (trustworthiness) to return back to the provider where $0 \leq z \leq 3y$ MU. The returned amount z represents the consumer's

[7] A great majority, 69%, of all transactions were first-time encounters. Overall, there occurred 272 distinct dyads and 394 transactions. Hence, each dyad met 394/272=1.45 times on average, and meeting only once was, in fact, most likely to be observed. Specifically, 161 dyads matched only once (59%), 100 dyads matched twice (37%), and 11 dyads matched three times (4%). Hence, $161{\cdot}1=161$ of all 394 transactions were one-time encounters (41%), $100{\cdot}2=200$ were two-times encounters (51%), and $11{\cdot}3=33$ were three-times encounters (8%).

[8] Due to a technical programming error, the restriction on sending requests blocked only one (rather than two) periods in four of the twelve experimental sessions. This led to the few instances with threefold transactions. Note that the four affected sessions included all four treatment conditions equally so that no systematic confound was caused.

behavior or the way the provider's asset is treated (e.g., tidy or devastated apartment). For any transfer y > 0, the provider hence faces exposure. The second and third steps of the transaction phase are identical to the original trust game (Berg, Dickhaut, and McCabe, 1995). A summary screen completes the transaction phase.

(III) Rating Phase—After completing the transaction phase, each consumer-provider dyad enters a rating phase in which they evaluate each other using a star rating score from 1 to 5 stars. Importantly, this phase does not exist for participants in the conditions without star ratings; they directly proceed to the next period.

Overview of Variables

Table 3.10 provides an overview of the independent (treatment structure) and dependent variables (measures) employed in the experiment, and how they align with our research hypotheses.

3.2.5 Procedure and Sample

The experiment was conducted at the experimental lab of a large European university. We recruited 144 participants (56 female, 88 male, average age=22.2 years, age range=18 to 36 years) from a student subject pool using the hroot system (Bock, Baetge, and Nicklisch, 2014). Informed consent was obtained from all participants, explicitly including permission to use the provided profile photos for scientific purposes. The experiment was implemented through a proprietary online environment based on standard web development languages (HTML, PHP, CSS). Written instructions were handed out to all participants and were read out aloud at the beginning of each session. Participants answered 6 quiz questions to ensure comprehension. For a summary of all instruction materials, see Appendix C.6 . Sessions took about 50 minutes on average. To incentivize behavior, monetary units earned within the experiment were converted into EUR at a rate of 4 MU=1 EUR. At the end of each session, 3 out of the 6 periods were selected for each subject at random and paid out in cash (average payoff=EUR 11.17). Table 3.11 provides sample demographics for each treatment. A set of ANOVAs confirms that none of these variables (age, gender, experience with peer-to-peer platforms) exhibits significant differences across treatments (Star Ratings: F_{AGE}(1,140)=.038, p=.845, F_{GENDER}(1,140)=.106, p=.745, F_{EXP}(1,140)=.039, p=.843; Profile Photos: F_{AGE}(1,140)=.350, p=.555, F_{GENDER}(1,140)=1.12, p=.292, F_{EXP}(1,140)=.547, p=.461).

Manipulation Check

To ensure that the experimental manipulation was successful, we conducted an ex post manipulation check using an online experiment. This confirmed that the tested artifacts (star ratings and profile photos) were (1) recognized at all and (2) perceived as cognitive (star ratings) and affective (profile photos) trust cues, respectively. To this end, we recruited 289 additional participants (166 female, 123 male, average age=33.62) from Prolific.ac (Palan and Schitter, 2018).

Table 3.10: Summary of independent and dependent variables in the experiment

Category	Variable	Description	Value scale/range
Independent Variables (Treatment Structure)	**Treatment:** Star Ratings (Cognitive Trust Cue)	Binary treatment variable to test H1a and H1b. In the *star rating condition*, participants evaluate each other in the rating phase (1 to 5 stars). In the *no star rating condition*, participants neither see a star rating nor do they rate their transaction partners.	{1=star ratings, 0=no star ratings}
	Treatment: Profile Photos (Affective Trust Cue)	Binary treatment variable to test H2a and H2b. In the *profile photo condition*, participants see a profile photo of the other participants. In the *no profile photo conditions*, participants were represented by a default image.	{1=profile photos, 0=no profile photos}
	Period	To test H1b and H2b, each participant engages in six periods of the experimental task. This allows to discern the dynamic interplay of cognitive and affective trust cues.	{1, 2, . . . , 6}
Dependent Variables (Measures)	Provider's Trusting Behavior	The *fraction y / 10* of the endowment the provider transfers to the consumer ($y \leq 10$ MU). This variable is a measure for the provider's trusting behavior (H1a/b, H2a/b).	[0, 1]
	Number of Ratings	The number of ratings a consumer or provider has received. This measure only exists in the star rating condition.	{0, 1, . . . , 5}
	Rating	The rating a consumer (/provider) has provided to evaluate a provider (/consumer) in the rating phase of the experimental task ("stars"). This measure only exists in the star rating condition.	{1, 2, . . . , 5}
	Average Star Rating Score	A consumer's or provider's average star rating score (rounded to the half unit). This measure only exists in the star rating condition.	{1.0, 1.5, . . . , 5.0}
	Consumer's Trustworthiness	The *fraction z / 3 y* of the available amount that the consumer transfers back to the provider ($z \leq 3y$ MU; step 3 of the transaction phase). The return is a measure for the consumer's trustworthiness.	[0, 1]
	Provider's Value π_{it}	$\pi_{it} = .5 + 1 + y_{it} \cdot (3z_{jt} - 1)$. The value (or payoff) a provider receives in period i, after having transacted with consumer j. This value is determined by the received booking fee ($.5$), the provider's endowment (1), their transfer to the consumer (y_{it}), and the relative return from the consumer (z_{jt}). Note that when no transaction occurs, this payoff is 1 (endowment).	[0.5, 3.5]

Table 3.11: Sample statistics on demographic control variables by treatment

Star Ratings	**Profile Photos**	**Age**	**Gender Female (yes/no)**	**Peer-to-PeerExperience (yes/no)**
		Mean (SD)	**Mean**	**Mean**
no	**no**	21.9 (2.43)	.417	.611
	yes	22.4 (3.04)	.333	.778
yes	**no**	22.2 (2.73)	.444	.722
	yes	22.3 (3.58)	.361	.694

Using an identical treatment structure and interface design, the manipulation check presented participants with a user profile of one potential transaction partner.[9] Following a general introduction on the experimental setup (i.e., the sharing transaction, rules, procedures), participants indicated to what extent the displayed user profile provided them with cognitive and affective trust cues (Table C.12 , Appendix C.7). Internal consistency for both the cognitive (Cronbach's α=.93) and the affective trust construct (α=.84) met the common threshold of .70 (Bagozzi and Yi, 1988).

The results of this manipulation check suggest that the experimental manipulation was successful (Table 3.12). Specifically, we can confirm that (1) star ratings were perceived as cognitive trust cues (β=3.22, p <.001), while (2) profile photos were perceived as affective trust cues (β=2.08, p <.001). At the same time, profile photos did not exhibit any significant effect on cognitive trust (β=.188, p =.404). While cognitive trust is driven by star ratings only, affective trust appears to be driven by both star ratings and profile photos. Even though star ratings appear to have an influence on the perception of affective trust cues (β=1.20, p <.001), this effect is outweighed by profile photos by a factor of almost 2. Importantly, we observe no interaction effects between star ratings and profile photos as both cognitive (β=-.226, p =.481) and affective (β=-.601, p =.070) trust cues.

Table 3.12: Manipulation check results

	DV=Cognitive Trust Cue		**DV=Affective Trust Cue**	
Star Ratings$^{(\text{yes}=1,\ \text{no}=0)}$	3.22	***	1.20	***
	(.223)		(.230)	
Profile Photos$^{(\text{yes}=1,\ \text{no}=0)}$	.188		2.08	***
	(.224)		(.231)	
Star Ratings × Profile Photos	-.226		-.601	
	(.320)		(.330)	
Intercept	2.50	***	2.27	***
	(.157)		(.162)	
Observations	289		289	
R2	.570		.345	

Note: Ordinary least squares regression models. DV=dependent variable; standard errors in parentheses; *** p<.001; ** p<.01; * p<.05

[9] To preserve the data privacy of the participants in the lab experiment, the profile photos used in the manipulation check study were generated using the generative adversarial network StyleGAN2 (Karras et al., 2020). All photos were then classified for demographic characteristics using the Microsoft Face and Emotions API. The final set of photos was selected to match our set of lab participants regarding their demographic characteristics (i.e., age, gender).

3.2.6 Results

Overall Treatment Effects on Trusting Behavior

As a first step of analysis, we consider the overall effects of star ratings (H_{1a}) and profile photos (H_{2a}) availability on the provider's trusting behavior (i.e., the transferred amount to the consumer). To be as specific as possible, we chose single transactions as the unit of analysis (n=394). Figure 3.9 depicts the positive effects of both cognitive and affective trust cues for the different treatment conditions at an aggregated level. A 2 × 2 ANOVA (Table 3.13) reveals significant effects for both star ratings ($F_{StarRatings}$(1, 390)=32.3), p <.001) and profile photos ($F_{ProfilePhotos}$(1, 390)= 38.5), p <.001) on trusting behavior while these variables do not significantly interact (p=.142). Providing initial support for H_{1a} and H_{2a}, post-hoc comparisons (Tukey HSD) confirm that trusting behavior is higher when star ratings (H_{1a}: Δ=.150, p <.001), and/or profile photos (H_{2a}: Δ=.164, p <.001) are available.

Table 3.13: Treatment effects of trust cues on trusting behavior

Trust Cue	ANOVA		Not Displayed			Displayed		
	F-score	p-value	Mean	SD	95% CI	Mean	SD	95% CI
Star Ratings (SR)	32.3	.001	.670	.326	[.625, .716]	.821	.213	[.791, .850]
Profile Photos (PP)	38.5	.001	.662	.315	[.618, .707]	.826	.226	[.795, .858]
SR × PP	2.16	.142						

Figure 3.9: Main treatment effects of trust cues on provider's trusting behavior
Note: Error bars indicate 95% confidence intervals.

Trusting Behavior over Time

Next, we focus on the role of time-dependency. As shown in Figure 3.10, the joint availability of star ratings and profile photos facilitates trusting behavior of about 75% in the first period. In comparison, the absence of both trust cues yields about 50%. In contrast, if only one of the two cues is present, first-period trusting behavior yields levels of 60–65%. While all other treatment conditions exhibit an increasing and roughly linear trend, the condition in which profile photos are present exhibits a markedly different pattern. Here, following an inverted u-shape, trusting behavior decrease back after an initial increase of up to almost 90%.

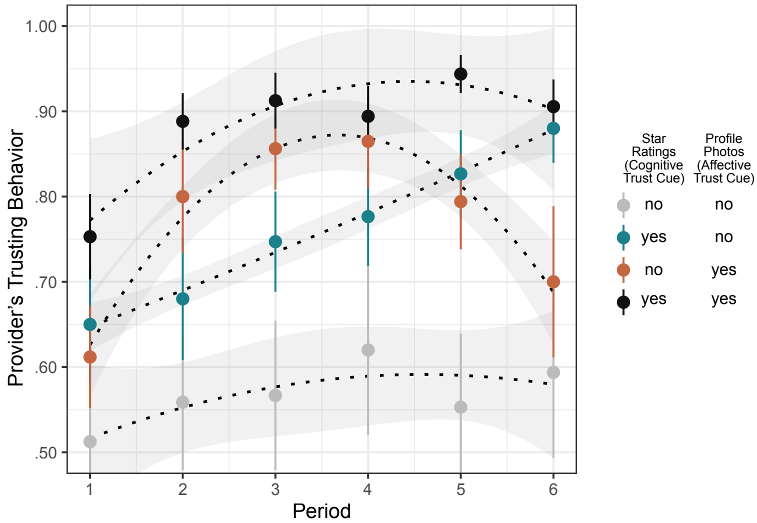

Figure 3.10: Course of provider's trusting behavior across periods
Note: Data on transaction-level, n=394; error bars indicate 95% confidence intervals.

To statistically assess this time-dependency, we consider a set of random effects panel regressions. In the first two models (Models I and II), we include linear time effects (see Table 3.14). Further, the model takes into account repeated measures (period 1 to 6)[10] per subject. The basic regression equation (Model I) is given as

$$y_{it} = \beta_0 + \sum_{n=1}^{5} \beta_n x_i^n + \beta_6 t + \epsilon_i + \mu_{it},$$

where y_{it} denotes the trusting behavior by participant i in period t. The variables x_1 and x_2 represent the treatment variables (ratings, profile photos), and x_3 to x_5 contain demographic information (i.e., age, gender, experience). Note that these factors are participant-specific and do not change over time (hence not depend on t). Furthermore, we control for period (t) to capture general time trends. Last, ϵ_i denotes the participant-specific error and μ_{it} the model error. Model I confirms the general treatment effects both of star ratings (supporting H_{1a}: β=.139, p <.01) and profile photos (supporting H_{2a}: β=.153, p <.01). Moreover, this model shows that there exists a positive overall time effect throughout the six periods (β=.019, p <.001).

Next, in order to control for the development over time, this basic model is extended by period-treatment interaction effects (Model II). Here, the period-treatment interactions show that the period-effect is predominantly driven by star rating conditions, which build up their effect over time (supporting H_{1b}: β =.023, p <.05) but have no significant effect in the first period yet (β =.083, p =.13). Conversely, profile photos

[10]Since we analyze the period variable's interaction with the treatment variables, these values are coded as 0 to 5 in order to be able to interpret the respective other variable's coefficients as first-period effects.

Table 3.14: Regression models

	DV=Provider's Trusting Behavior											
					III(a)		III(b)		III(c)		III(d)	
	Model I		Model II		Subsets (Trust Cues)							
					None		Only Ratings		Only Photos		Ratings + Photos	
Star Ratings$^{(yes=1,\ no=0)}$	H_{1a} **.139**	**	.083									
	(.051)		(.055)									
Profile Photos$^{(yes=1,\ no=0)}$	H_{2a} **.153**	**	**.152**	**								
	(.052)		(.056)									
Period$^{(0–5)}$	**.019**	***	.008		.041		**.057**	**	**.174**	***	**.085**	***
	(.005)		(.008)		(.041)		(.019)		(.037)		(.019)	
Period^2					-.008		-.004		**-.032**	***	**-.012**	***
					(.008)		(.004)		(.007)		(.004)	
Star Ratings × Period			H_{1b} **.023**	*								
			(.009)									
Profile Photos × Period			H_{2b} .001									
			(.009)									
Gender$^{(female=1)}$	-.055		-.055		-.176		.014		-.012		.016	
	(.054)		(.053)		(.151)		(.111)		(.107)		(.071)	
Age	.009		.009		.021		-.006		.017		.001	
	(.008)		(.008)		(.032)		(.019)		(.018)		(.008)	
Experience$^{(yes=1)}$	.069		.068		.093		.202		.037		-.061	
	(.056)		(.056)		(.159)		(.110)		(.127)		(.077)	
Intercept	.318		.348		.086		.661		.239		**.791**	***
	(.187)		(.185)		(.727)		(.406)		(.397)		(.217)	
Observations	394		394		96		97		100		101	
R^2	.086		.102		.029		.317		.209		.254	

Note: Generalized linear models with subject random effect. DV=dependent variable; standard errors in parentheses;
*** p.001; ** p.01; * p.05

have an immediate effect right from the start (β =.152, p <.01), which then, however, is time-invariant. Hence, H2b is not supported (β <.001, p =.997)—at least when assuming a *linear* trend.

As clearly suggested by Figure 3.10, this assumption of linearity, however, does not hold as there appears to exist a clear curvilinear progression when profile photos are present. In Models III a-d, we hence introduce quadratic period effects. In order to avoid uninterpretable triple interactions (PP × SR × (t + t^2)), we estimate four separate models for each of the 2 × 2 treatment conditions in Models III(a)-III(d). Naturally, the treatment variables are not part of these models. These analyses show *that both conditions with profile photos exhibit a curvilinear structure* with positive and significant linear estimates (β =.174, p <.001; resp. β =.085, p <.001) and negative and significant second-order estimates for period (β =-.032, p <.001; resp. β =-.012, p <.001). When only star ratings are present, there is a "simple" linear and positive time-trend (β =.057, p <.01). In the setting with neither profile photos nor star ratings, no significant time effect occurs, albeit the direction is slightly positive (β =.041, p =.32).

None of the control variables (gender, β =-.055, p =.303; age, β =.009, p =.279; experience, β =.069, p =.224) exert significant effects on trusting behavior. Note that we abstain from including the interaction between the treatment variables in the panel models (let alone the triple interaction Star Ratings × Profile Photos × Period) as there were no significant interactions between affective and cognitive trust cues (see Table 3.13 above).

The Different Effect Components of Star Ratings

We have now established that the presence of a star rating system has a significant effect on trusting behavior. Note, however, that there may be different factors at play since star ratings play a multi-layered role. First, the presence of a star rating allows for an improved assessment of one's counterpart (i.e., the consumer in this case) as some historic information about their behavior is displayed. Moreover, it may allow for higher degrees of provider's trusting behavior since malicious exploitation of this trust could be penalized by means of the rating system (ex post). Note that there even exists a third aspect. Since the rating system works in a mutual way, also the provider will have to take into account that he or she will be rated after the transaction by the consumer. The anticipation thereof may, additionally, increase the exhibited trusting behavior (ex ante).

Hence, it is important to delineate these effect components in order to assess which fractions of the observed trusting behavior are actually due to the displayed rating scores (i.e., the net effect). As a next step, we hence consider how trusting behavior evolves over the course of the six periods for the star rating treatment condition. Note that providers exhibit substantial trusting behavior even in the treatment condition in which no trust cues whatsoever are displayed ("baseline" condition). In fact, in this condition, providers transfer about half of their endowment (51.3%) to consumers on average. Moreover, there exists a slightly increasing trend. We capture this by the *General Trust Baseline* and the *General Time Effect* (see Table 3.15 and Figure 3.11). Also, note that in the very first period ($t=1$), participants in the star rating conditions were not able to draw on specific rating scores because no participant had had the chance to collect ratings at that point. Nevertheless, we still observe higher first-period trusting behavior as compared to participants in the non-star-rating conditions. This effect, which we label as *Damocles Effect*, indicates that the mere existence of the star rating system (even without the display of actual rating scores) facilitates trusting behavior due to the anticipation of rating and being rated as outlined above. Making use of this temporal distinction, we can further subtract the Damocles effect in all subsequent periods ($t \geq 2$), yielding a residual (red lines in Figure 3.11). This residual can be considered as the *Rating Score Net Effect*. We observe that the net effect increases only slowly within the first four periods and then jumps to a level of about .15, comparable in size to the Damocles Effect. This observation provides further evidence for H_{1b}, but also suggests that the impact of time (and/or the number of underlying ratings) on the net effect of an aggregated star rating score is more complex than a simple linear trend, maybe non-linear or involve discontinuities.

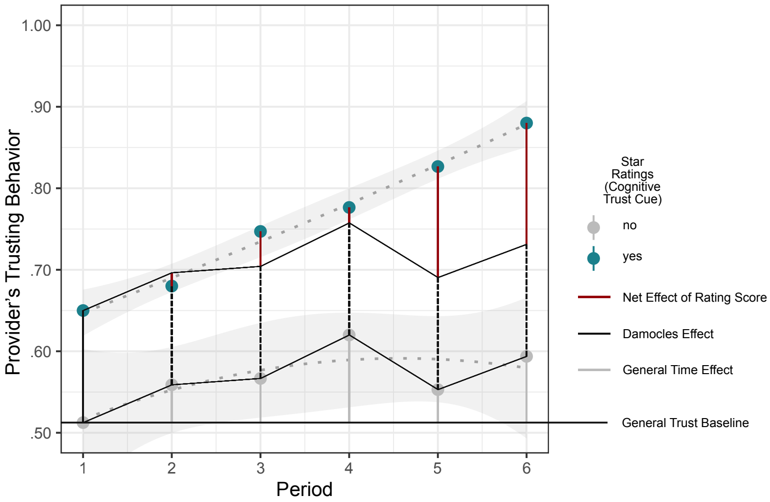

Figure 3.11: General Trust Baseline and resulting Damocles effect, Net Effect of Rating Score, and General Time Effect across periods

Table 3.15: Delineation of star rating's effect on trusting behavior

Effect Delineation		Period 1	2	3	4	5	6
General Trust Baseline	The trusting behavior in the first period of the baseline condition (without star ratings and without profile photos)	.513	.513	.513	.513	.513	.513
Time Effect	The effect of time on trusting behavior in the baseline condition (without star ratings and without profile photos)	—	.046	.054	.108	.040	.081
Damocles Effect	Level of trust behavior in the first period of the star rating condition	.138	.138	.138	.138	.138	.138
Net Effect of Star Rating	The residual between the actually observed trusting behavior in the star rating condition and the sum of the *General Trust Baseline*, the *General Time Effect*, and the *Damocles Effect*	—	-.016	.043	.019	.136	.149
Total Effect		.138	.168	.235	.265	.314	.368
Result		.651	.681	.748	.778	.827	.881

Complementary Analyses

Star Ratings and Trusting Behavior (Appendix C.1)—Overall, our data show that the rating distribution in our study is consistent with what is typically observed on contemporary platforms. Moreover, the analysis reveals that the ratings providers and consumers receive depend on their respective behavior (i.e., the amount they transfer or transfer back). Importantly, also consumers' chances of being accepted as well as providers' trusting behavior depend on the consumer's aggregated star rating score. Hence, behavior is reflected in star ratings and, vice versa, star ratings affect behavior.

Visual Photo Properties and Trusting Behavior (Appendix C.2)—Similar to the analysis of specific star rating scores, we consider how specific visual properties of the profile photos, such as face visibility, attractiveness, and visual trustworthiness, affected trusting behavior. However, we did not find any evidence for significant effects with regard to these attributes.

Consumers' Returns (Appendix C.3)—While the focus of this work is on (providers') trusting behavior, we also considered consumers' trustworthiness as operationalized by the amounts they returned back to the provider. Typically, this analysis is secondary and relatively straight forward, "as it tends to be overwhelmingly driven by the amount invested by the sender" (Bapna et al., 2017, p.120). In fact, we find that the presence of both types of trust cues has a positive effect on returns, whereas the effect of profile photos is limited to the first periods.

Value Decomposition (Appendix C.4)—Combining the findings of trusting behavior (providers' behavior) and ex post trustworthiness (consumers' behavior), we can decompose the overall value providers receive along these (factorial) partial effects. This analysis grants further insight into how specifically the trust cues "generate" value. For instance, we find that while overall, trusting behavior is similar when either one or the other cue type is present, the presence of star ratings yields higher trustworthiness. This treatment difference can hence be attributed to the ratings' effect on consumers rather than provider behavior.

Matches and Requests (Appendix C.5)—Both across treatments and periods, we observe non-significant differences with regard to the number of matches (i.e., transactions). The matching rate exceeds 90% throughout the experiment, so that basically every participant is matched in almost every period. However, both star ratings and profile photos have positive effects on the share of participants who sent at least one request. But, as there are no significant effects on the fractions of participants who received at least one request, the additional requests cannot be distributed evenly but concentrate on those who already receive requests from other participants. Consequently, this does not result in differences in the number of matches. Period did neither affect the number of matches or request behavior.

3.2.7 Discussion

The number of peer-to-peer sharing platform businesses is ever-growing. Airbnb, Blablacar, or Drivy are already shaping a substantial part of today's e-commerce landscape with a steadily increasing share (Mittendorf, Berente, and Holten, 2019). At the same time, maintaining trust among participants is of the utmost importance for the continued existence of these platforms, particularly for emerging ones (Hodapp, Hawlitschek, and Kramer, 2019). With our paper, we provide novel insights into the interplay of cognitive and affective trust cues over time.

Cognitive Trust Cues over Time: The Effect of Star Ratings

In the very first period of the experiment, participants in the star rating conditions were not yet able to draw on any rating scores. Still, in these conditions, we observe more intense trusting behavior (i.e., higher transfers) as compared to the non-star-rating conditions. This finding reflects previous research such as Rice (2012), who distinguishes between the trust-building effect of the mere existence of a rating system and specific scores. Our findings indicate that the existence of star ratings (even without displaying any scores) positively affects trusting behavior (H_{1a}). We offer a potential explanation for this observation based on participants' anticipation of ratings—the *Damocles Effect*. In a sense, the prospect of leaving a rating and being rated seems to represent a mutually impending threat, causing participants to exhibit trusting as well as trustworthy behavior. Next, the effect of star ratings on trusting behavior becomes stronger over time (H_{1b}). The fact that star ratings seem to represent a reliable cue, and that their effect is steadily increasing for increasing numbers of underlying ratings, is consistent with previous research (Burtch, Ghose, and Wattal, 2014; Cabral and Hortaçsu, 2010).

Affective Trust Cues over Time: The Effect of Profile Photos

Interestingly, we find that that the effectiveness of profile photos for engendering trust seems to follow an inverted u-shape over time. Profile photos start out to function as a powerful trust cue early on (clearly surpassing the effectiveness of star ratings alone), and this effectiveness then increases further. Overall, they exert a positive influence on trust behavior (H_{2a}). However, being the sole cue, the trust-promoting capability of profile photos collapses back to its origin level later on. Indeed, after the fourth period, the power of profile photos seems to be eroding. The fact that this pattern can be observed in both photo conditions (i.e., with and without star ratings) is not only an indicator for the reliability of this result but also highlights the importance of viewing it from a dynamic (rather than static) perspective. We suggest that the eventual decrease of trusting behavior is driven by the drop in returns, which can be observed between period 3 and 4, at the peak of the trusting behavior curve (see Figure C.7, Appendix C.4). This drop precedes the downward slope in the inverted u-shape curve. From an ELM perspective, this drop can be interpreted from two perspectives:

First, it implies emerging exploitation of providers' trusting behavior by consumers. This exploitation can be interpreted as a counterargument that burdens the positive effect of the affective trust cue. Second, as part of the ELM, Petty and Cacioppo (1986) describe an "elaboration continuum," which states that the mode of information evaluation is not subject to a strictly binary classification but rather a continuous scale. As such, the mode of processing the affective cue may shift across transactions. Conceivably, overall trusting behavior may be subject to two partial effects: (1) *experience* or confidence within the environment, and (2) the cue's *evidenced effectiveness*. Initially, participants have no or little experience/confidence within the transactional environment (and, naturally, with the experimental setup too). This may lead them to be rather cautious and, as a consequence, show limited trusting behavior (i.e., make low transfers). At the same time, they may have rather high expectations regarding the cue's effectiveness (or informational value). Throughout the experiment, these values shift where, naturally, participants gain confidence with each transaction and period but—at the same time—experience that profile photos may not (always) live up to the high expectations they put in them (e.g., when their transaction partner disappoints the trust they put in them by, say, a zero return). Since both factors are required, it can be argued that *trusting behavior emerges as the interaction* of both. Given that one factor (i.e., experience) increases monotonically (e.g., from some level close to zero) and the other factor (i.e., evidenced effectiveness) decreased monotonically (e.g., towards some level close to zero), the result is a curvilinear progression of trusting behavior (inverted u-shape). Of course, this merely represents a potential explanation at this point, but it may offer a rationale for the observed data. Future research will have to examine the particular levels and courses of experience and evidenced effectiveness as well as their interaction and effects on trusting behavior.

Overall, the finding of the inverted u-shape suggests that profile photos convey varying effects on trust, depending on the specific phase of transactions. Our results thereby extend previous research, which has often abstracted from such potential time-dependencies of interpersonal trust (Bapna, Qiu, and Rice, 2017; Gefen, 2000; Gefen, Karahanna, and Straub, 2003; Pavlou and Gefen, 2004).

Dynamic Complementarity of Cognitive and Affective Trust Cues

To some extent, cognitive and affective trust cues *complement* each other over time. In contrast to star ratings, profile photos allow a "kick-starting" of trust in early phases in which star ratings are less accurate and reliable, helping to overcome this cue's inherent "cold-start problem" (Wessel, Thies, and Benlian, 2017). However, the presence of both trust cues leads to higher trusting behavior than when only one is available. Interestingly, the cues do not significantly interact (Table 3.13) and have an additive effect. This non-dependence of cues can be interpreted as support for the assumption that the cues are processed through different mental paths. In fact, Petty and Cacioppo (1986) already pictured this additivity when combining centrally and peripherally processed information for one-time exposure—a presumption that seems to hold and extend to exposure throughout multiple periods in our experiment.

Theoretical Contribution

Our study provides theoretical contributions to research addressing trust on peer-to-peer sharing platforms. Previous research widely agrees that the effects of trust cues on trusting behavior are relatively stable and comparable across different phases of their "lifecycle" as their effects are time-invariant. To this end, McKnight and colleagues have theorized that certain trust cues may indicate stability through structural assurances and situational normality (McKnight, Choudhury, and Kacmar, 2002; Mcknight, Cummings, and Chervany, 1998). Only recently, the issue of longitudinal examination of trust cues has drawn attention outside the IS community (Werff and Buckley, 2017). Yet, previous research does not sufficiently capture on how the trust-building capacity of cognitive and affective trust cues on trusting behavior may be subject to dynamics across multiple periods and/or transactions.

Drawing on the ELM (Petty and Cacioppo, 1986; Petty, Cacioppo, and Schumann, 1983), we extend research on cognitive and affective trust cues by taking a "dynamic" perspective. We do so by drawing on the central and peripheral route of information processing, as outlined in the ELM. In line with our theoretical reasoning, assumptions about stable or increasing effects of trust cues apply to star ratings (cognitive trust cues), associated with the central route of information processing but not to profile photos (affective trust cues), associated with the peripheral route—their time-dependency shows a non-linear pattern.

Rather than assessing their trust-building potential in isolation (Komiak and Benbasat, 2006; Stewart and Gosain, 2006), we analyze the combination and interplay of two specific types of cues. Thereby, we follow the plea of previous ELM research, stating that "much more research is needed to examine the roles of [information] repetition and [information] variation" and that "researchers and practitioners would benefit from a better understanding of the degree to which the attitudes created or changed by their efforts persist over time, resist change, or predict behavior" (Schumann et al., 2012, p. 62). We investigate trust-building through the respective trust cues as a dynamic process over time, using an experiment with multiple transactions. Showing that cognitive and affective trust cues exhibit time-dynamic complementarity, our findings indicate that previous research may have underestimated the role of affective trust cues so far as they play an important role in complementing cognitive cues—in particular in the earlier stages.

Methodological Contribution

Our study offers a distinct methodological contribution. Specifically, we extend the trust game (Berg, Dickhaut, and McCabe, 1995) to the context of peer-to-peer sharing platforms, by providing a controlled experimental setting in which the emergence of trust can be investigated over the course of multiple periods. Complementary to the existing approaches drawing on surveys (Ert, Fleischer, and Magen, 2016) or field data (Edelman, Luca, and Svirsky, 2017; Fradkin, Grewal, and Holtz, 2018), our experimental setup provides a proxy for understanding user behavior on peer-to-peer sharing platforms, particularly when considering how trusting behavior evolves dynamically over time. Our experimental design complements previous research by allowing for a more natural investigation of transactional behavior. In contrast to prior studies, we use a "natural" endogenous process of matchmaking with requests and responses, similar to what is observed on many (if not: most) actual peer-to-peer sharing platforms (see Table 3.8).

Managerial Implications

The results of our study have important implications for consumers, providers, and managers of peer-to-peer sharing platforms. Specifically, our results show that the relative importance of cognitive and affective trust cues is not stable but changes over time. On the one hand, this time-dependency emphasizes the importance for platform managers to actively encourage consumers and providers early on to upload profile photos as a means to kick-start the formation of trust—particularly during the initial and early stages of platform evolution. On the other hand, it is important for platform managers to understand that the beneficial effect of profile photos wanes off over time. Clearly, because of this dynamic interplay over time, it is vitally important to encourage users to make active use of both types of trust cues instead of overly relying on one or the other. It also emphasizes the dual role of human information processing vial central and peripheral challenges, both of which need to be considered in platform design. While our study focused specifically on peer-to-peer sharing scenarios with free market-based requests-and-response process (endogenous matching) and highly transactional exchanges (e.g., Airbnb, see Appendix C.7), there is reason to believe that our results may provide insights for a broader range of peer-to-peer sharing platforms. While platforms such as Airbnb actively encourage their users to upload profile photos and to evaluate each other by means of ratings after each transaction, there exist other platforms such as Craigslist or Gumtree (some of the most popular peer-to-peer platforms in the US, the UK, and Australia) that do not enable their users to provide such cues. Furthermore, on some platforms, even if they allow their users to upload personal photos, this option is far from being used by everyone (Hesse et al., 2020). Uber have even experimented with forcing users to leave a rating, for instance, by requiring them to provide feedback before allowing them to engage in another transaction. As most peer-to-peer sharing platforms' business models are provision-based—and hence hinge on the realization of transactions—they may eventually benefit from facilitating the use of a range of trust cues to their users.

Limitations and Future Work

Alike any research, this study exhibits several limitations, some of which, however, provide viable starting points for future work.

Dual role of star rating—The availability of star ratings may have a dual effect on behavior. While users observe the ratings of others and can make inferences to their past behavior and trustworthiness from that, they are also aware of the fact that (1) they *themselves* will be rated after a transaction and (2) will be able to rate (i.e., to reward or punish) their transaction partner. This should be kept in mind when investigating star rating's impact on trusting behavior. To separate such potentially confounding effects, one may consider trusting behavior in the very first period, where no user has accumulated any reputation yet, but the prospect of the mutual rating process casts its shadows before. As shown in Table 3.14 (Model II), the availability of star ratings does not affect trusting behavior in the first period, suggesting that the trust-enhancing effect is rooted in the available score rather than in prospects of being evaluated oneself or being able to evaluate the other user.

Congruency of period and ratings—Since virtually all participants engaged in a transaction in almost any period (the overall fraction of realized transactions is 91% and varies only negligibly between treatments), some caution is required concerning the process of trust-building which may root either in *time* or the *number of ratings*, or both (using both variables in the regression models would be subject to collinearity issues). While there is some rationale for time- or period-contingent trusting behavior (e.g., gaining experience and hence confidence in the processes and other users overall), the underlying number of star ratings too represents a very plausible explanation for trust (i.e., cue accuracy and reliability). Artificially preventing participants from conducting a transaction each period could help to disentangle these factors.

External validity—While our study is based on actual and incentivized user behavior and hence provides valuable insights into the formation of trust, it is still conducted within an artificial laboratory environment and without framing to a particular application context. In contrast to actual real-world transactions, there occurs no physical interaction down the line, such as, for instance, a stay in someone's apartment, renting their car, or sharing a ride. The interpretation of our findings hence requires some caution with regard to transferability to actual transactions for platforms in the wild.

Dynamic effects of other trust cues—Our study provides a sound understanding of the effects of star ratings and profile photos, common examples of cognitive and affective trust cues, over time. However, future research should consider to also investigate the effects of other established trust cues (e.g., labels, badges, certificates, text elements, videos). From the perspective of a peer-to-peer sharing platform provider, it is essential to leverage a portfolio of trust cues, which add up to an overall trust enhancing effect that is effective over the whole platform evolution. We encourage future work that addresses this need in experimental studies grounded in ELM.

3.2.8 Concluding Note

Both cognitive (e.g., star ratings) and affective (e.g., profile photos) trust cues represent effective means for trust-building in peer-to-peer sharing platforms. While we find no evidence for an interaction of these cues, they complement each other over time. Our findings inform both platform operators and users attempting to support and sustain trust in such environments. Furthermore, our experimental design may serve as a basis for scholars seeking to further investigate trusting decisions within the emerging platform economy landscape.

3.3 Blockchain and Trust in the Platform Economy: The Case of Peer-to-Peer Sharing

The previous two studies investigated how individual UR influences P2P platform users' perception and behavior. However, the underlying technological layer of a platform is likely to influence users as well. As an innovation of the 21st century, the blockchain may provide the foundation for trust-free systems and market exchanges. The next study reports a scenario-based online survey with participants taking the role of a customer on a blockchain-based P2P platform. The results confirm that while trust in peers and shared products have no overall significant effect on transaction intentions, trust in blockchain technology and the community of blockchain users drive rental intentions mediated by trust in the blockchain-based platform. The study sheds light on how established trust relationships shift from a peer and product focus towards trust in platforms and their underlying technology.

David Dann, Florian Hawlitschek, Christian Peukert, Carl Martin & Christof Weinhardt[11]

3.3.1 Introduction

The emergence of thriving platforms (e.g., eBay, Airbnb, Uber) diversifies and changes e-commerce (Sundararajan, 2016; Van Alstyne, Parker, and Choudary, 2016). Nascent platform ecosystems crucially depend on a careful balance of aspects such as openness and control, adequate value capture mechanisms, and, importantly, on building trust (Hodapp, Hawlitschek, and Kramer, 2019). Within the broader platform economy, peer-to-peer (P2P) sharing platforms are particularly flourishing (Dann, Teubner, and Weinhardt, 2019). The "sharing economy" is a multifaceted concept that is associated with ideas ranging from social and sustainable world improvement to a future of neoliberal platform capitalism. Following the European Commission, we understand it as an environment for users to (fee-based) grant one another access to underused resources (Frenken and Schor, 2017). The European Commission expects annual spending of €27.9bn on P2P platforms within the EU-28 states (European Commission, 2016). This domain differs from traditional e-commerce insofar as offers and services on P2P platforms are often run by private individuals. Consequently, users face economic exposure caused by unreliability or fraudulent offers that undermine the fundamental collaborative mindset of the sharing economy (AirbnbHell, 2019), making one factor particularly decisive: trust—so to speak the quintessence of the sharing economy (Gebbia, 2016; Hawlitschek, Teubner, and Weinhardt, 2016; Möhlmann and Geissinger, 2018).

Trust itself is an area of research considered from various angles, which, in turn, resonates with versatile concepts and theories for addressing it. For the connection of trust with the sharing economy, literature highlights the relationship between three main sides: Peers, products, platforms (Hawlitschek, Teubner, and Weinhardt, 2016; Hawlitschek et al., 2016b; Möhlmann, 2016). In this work, we focus on trust from the perspective of the platform's underlying technology. Söllner, Hoffmann, and Leimeister

[11] This study was published in the *WI 2020 Proceedings*, `https://doi.org/10.30844/wi_2020_n2-dann`, (Dann et al., 2020a).

(2016) demonstrate that trust in the environment enabling the platform is an antecedent for trusting the platform provider. Beyond the Internet, the typical technological layer, which enables the sharing economy (Hamari, Sjöklint, and Ukkonen, 2016), new environments for enabling P2P sharing platforms are arising—among these, the blockchain is probably the most popular (Hawlitschek, Notheisen, and Teubner, 2018; Seebacher and Schüritz, 2017). The blockchain is attributed to affect trust (Beck, 2018) and, beyond that, to be the technology that is capable of establishing true trust-free sharing economy environments (Lundy, 2016; Glaser, 2017).

Against this backdrop, we shed first light on trust relationships in a blockchain-enabled sharing economy environment. Our overarching research question is:

RQ: *How do blockchain-enabled platforms frame consumers' trust perception and their intention to enter a transaction?*

To answer this question, we develop our research model building on a previous pilot study from Hawlitschek (2019) and substantiate it with a more representative sample. In addition, we conduct further analyses on demographic and character trajectories and provide insights from qualitative analyses. Overall, we argue that a platform that includes a blockchain mechanism functions as a prospect of a trustable technological environment where users are more willing to enter transactions. Using a scenario-based online survey, we assess individual effects of both blockchain technology- and community-related aspects on trust in the platform, its peers, and its products and, ultimately, how this connects to their willingness to enter a transaction.

3.3.2 Related Work and Theoretical Background

The P2P sharing economy serves as a hypernym for a variety of platforms, activities, and services (Hamari, Sjöklint, and Ukkonen, 2016). As a sub-category of e-commerce, it is also subject to the fact that the facilitation of transactions via the Internet lacks the development of social and economic bonding to induce trust between the transaction partners (Bolton, Katok, and Ockenfels, 2004b). Furthermore, while in traditional e-commerce, users mainly interact with professional vendors (B2C), transactions on P2P sharing platforms rely upon two private individuals (Hawlitschek, Teubner, and Gimpel, 2016). These individuals usually have not met face to face before (Jones and Leonard, 2008), and, typically, interact with each other for the first time (Teubner, 2018). The mere existence of mutual trust between these two peers, however, is not sufficient to engender a transaction, if it takes place within an environment that is perceived as untrustworthy (Sundararajan, 2016; Möhlmann, 2016; Einav, Farronato, and Levin, 2015; Weber, 2014). Consequently, to understand trust relationships on P2P sharing platforms, trust needs to be considered from a threefold perspective—peers, platforms, and products (Hawlitschek, Teubner, and Weinhardt, 2016).

This renders trust a crucial element for a P2P sharing platform. Also referred to as the "most often used word in any debate about the sharing economy" (Nesta, 2016), it is a widely discussed topic in literature.

To induce trust, platform operators incorporate reputation mechanisms (e.g., star ratings, text reviews, profile images) to establish trust in the products or services offered as well as in the individual peers (Dann, Teubner, and Weinhardt, 2019; Teubner and Dann, 2018). Nevertheless, the potential of reputation mechanisms is limited. Star ratings, the most popular among these, are subject to a positive bias, in which users tend to award the maximum rating (Teubner and Dann, 2018; Ert, Fleischer, and Magen, 2016; Ke, 2017b; Slee, 2013). On Airbnb, for instance, the average rating of close to 95% of all listings is between 4.5 or 5.0 stars, and virtually no listing has a standing rating of 3.5 stars or below (Zervas, Proserpio, and Byers, 2015). Moreover, this positivity bias also applies to text reviews (Teubner and Dann, 2018; Zervas, Proserpio, and Byers, 2015), diminishing the informative power of these mechanisms. Even self-generated reputation mechanisms such as profile images are subject to unwanted side effects. While profile images are found to engender trust in the formation of a transaction (Bridges and Vásquez, 2018), they may foster discrimination, a typical phenomenon on P2P sharing platform (Edelman and Luca, 2014; Edelman, Luca, and Svirsky, 2017). This becomes particularly evident, considering that the majority of peers on those platforms reveal their faces with their self-uploaded profile images (Teubner and Dann, 2018).

Beyond trust induced by reputational mechanisms, trust may be induced from a technological angle (Söllner, Hoffmann, and Leimeister, 2016). The blockchain, also referred to as a "trust machine" (The Economist, 2015), promises to revolutionize P2P platforms and enable "trust-free" systems (Greiner and Wang, 2015). Despite calls to examine the blockchain technology in the context of P2P platforms (Sundararajan, 2016; Beck, Müller-Bloch, and King, 2018; Risius and Spohrer, 2017; Gertz, Puschmann, and Alt, 2016; Notheisen, Hawlitschek, and Weinhardt, 2017), Information Systems literature on blockchain-driven trust in this context is scarce (Hawlitschek, Notheisen, and Teubner, 2018; Seebacher and Schüritz, 2017). Previous research mainly considers blockchain-based systems from a cryptocurrency (e.g., Bitcoin) perspective (Auinger and Riedl, 2018; Sas and Khairuddin, 2015; Ahangama and Poo, 2016; Ahangama and Poo, 2016; Ahangama and Poo, 2016; Ingram and Morisse, 2016; Ingram and Morisse, 2016), relies on simulation-based evidence (Tumasjan and Beutel, 2019), or constitutes conceptual work (Mehrwald et al., 2019).

Summarizing, studies on the perceptual, intentional, and behavioral effects within the intersection of trust on blockchain-enabled P2P platforms remain scarce. Thereby, our study addresses a research gap by providing evidence on the causal effects of a blockchain-enabled platform on trust perception and their transaction-fostering potential.

3.3.3 Research Model and Hypotheses

We analyze the influence of blockchain as an underlying technology for P2P platforms on transaction intentions and corresponding trust perceptions, by replicating and extending Hawlitschek's pilot study (Hawlitschek, 2019) of trust relationships in a blockchain-enabled sharing scenario (see Figure 3.12).

The model is based on the well-established work of Söllner and colleagues 2016, which suggests a model of trust in the context of general IS usage. We adapt their model by replacing trust in the Internet with trust in blockchain technology and trust in the community of Internet users with trust in the community of blockchain users. Next, we replace intention to use with intention to rent as a proxy for the intention to enter

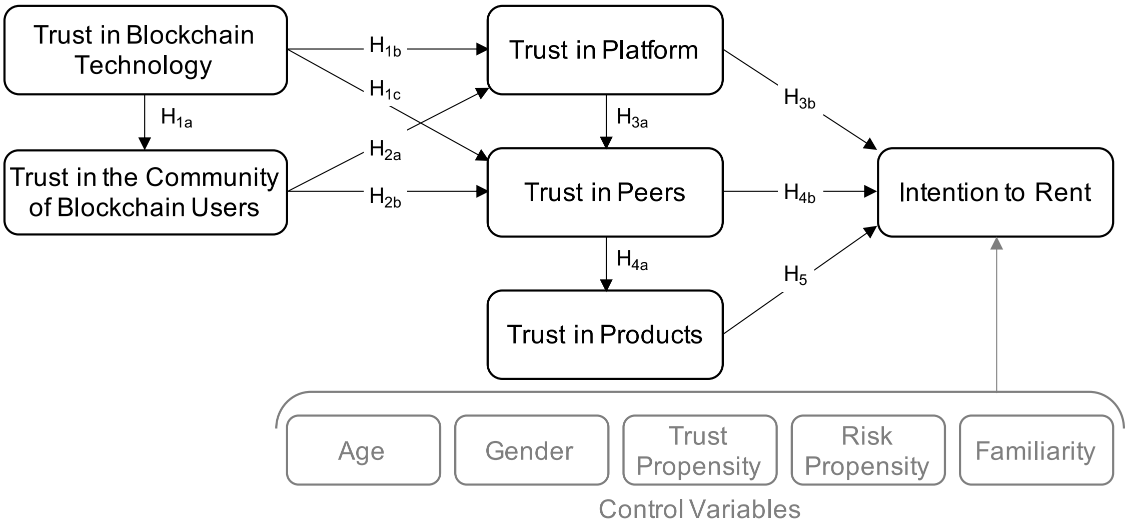

Figure 3.12: Research Model of Hawlitschek, Teubner, and Weinhardt (2016).

a transaction. Last, to adapt the model to the context of P2P sharing platforms, we replace the constructs trust in the information system and trust in provider with the 3P model from Hawlitschek, Teubner, and Weinhardt (2016).

Following the argumentation of Söllner, Hoffmann, and Leimeister (2016), we hypothesize that trust in blockchain technology has a positive effect on three targets—that is trust in the community of blockchain users, trust in platform, and trust in peers. The rationale behind these hypotheses is that people tend to trust more in other parties if they act in a trustworthy environment (Söllner, Hoffmann, and Leimeister, 2016). This environment can be the Internet—as in the study of Söllner, Hoffmann, and Leimeister (2016)—but also a blockchain-based environment.

H_{1a}: *Trust in blockchain technology has a positive effect on trust in the community of blockchain users.*
H_{1b}: *Trust in blockchain technology has a positive effect on trust in platform.*
H_{1c}: *Trust in blockchain technology has a positive effect on trust in peers.*

As Söllner, Hoffmann, and Leimeister (2016) argue, IS often depend on services or content provided by members of the community of internet users, and thus, trust in an IS increases with the trust in the community. We argue that the same holds true for blockchain-based platforms. The effect might even be more prevalent since the community of blockchain users (in many cases) directly contributes to the core functionalities of the blockchain-based platform itself by contributing to the consensus mechanism. At the same time, it is likely that a contributor to the consensus mechanism is at the same time also a user of the platform, and thus, trust in the community will also positively affect trust in peers.

H_{2a}: *Trust in the community of blockchain users has a positive effect on trust in platform.*
H_{2b}: *Trust in the community of blockchain users has a positive effect on trust in peers.*

The 3P model of Hawlitschek, Teubner, and Weinhardt (2016) suggests that the three targets of trust in peer, platform, and product have positive effects on transaction intentions in the sharing economy. Likewise, trust transfer theory suggests that trust may well be transferred between different sources, such as platforms and peers in the sharing economy (e.g., Teubner, Hawlitschek, and Adam, 2019) or peers and their offered products.

H_{3a}: *Trust in platform has a positive effect on trust in peers.*
H_{3b}: *Trust in platform has a positive effect on intention to rent.*
H_{4a}: *Trust in peers has a positive effect on trust in products.*
H_{4b}: *Trust in peers has a positive effect on intention to rent.*
H_5: *Trust in products has a positive effect on intention to rent.*

3.3.4 Method & Procedure

To test our research model, we conduct an online survey among a sample of Millennials of IS students (undergraduate) recruited at the Karlsruhe Institute of Technology using the organizing and recruiting software hroot (Bock, Baetge, and Nicklisch, 2014). For our study, using a well-educated student sample is reasonable, as this group of people represents one of the main user groups on P2P platforms (Godelnik, 2017; Ranzini et al., 2017; European Union, 2017; PwC, 2015; Akbar, Mai, and Hoffmann, 2016). First, participants were introduced to a blockchain-based P2P sharing platform. This introduction to the scenario was conducted by means of a written text and a subsequent video outlining the vision of a blockchain-based P2P sharing platform utilizing IoT assets—the Slock.it platform (https://slock.it/). Second, participants answered a questionnaire of fully randomized survey items (previously validated by Hawlitschek, 2019). To ensure content validity, the operationalization of all constructs follows established scales from literature (see Table D.13). Additionally, we control for demographic and trait information, including risk propensity (Dohmen et al., 2011), disposition to trust (Gefen, 2000), familiarity with blockchain technology, age, gender, and highest education degree. We further included multiple attention checks, as well as language proficiency, to ensure a high level of quality among the answers. Participants were incentivized with monetary rewards (equaling €10.39/hour per person).

3.3.5 Results

Due to the exploratory research objective of the study and the inclusion of formative scales in the model, we employ Partial Least Squares Structural Equation Modeling (PLS-SEM) for the analysis (Hair et al., 2016; Gefen, Straub, and Rigdon, 2011). We follow the two-stage approach by Hair et al. (2016) to analyze and interpret the research model.

Data collection took place in May 2019. Initially, 177 participants provided complete answers to the survey. Due to incorrect answers to one or more of the control questions, we excluded 16 participants from further analysis. The final sample consisted of 161 participants, a sample size adequate to detect small-sized effects with a power of .80

and alpha of .01 (Cohen, 1992).

Within the sample, the average age was 23.30 (SD=3.44), and among the participants, about 35% were female. The survey lasted, on average, 16.14 minutes (SD=3.60). The results for risk propensity (mean=6.22, SD=1.96; measured on an 11-point scale ranging from 0: not at all willing, to 10: very willing to take risks) indicates that the sample's average tends to be willing to take risks. Regarding disposition to trust, the sample's mean value is 3.97 (SD=1.27; 7-point Likert scale with the endpoints 1: strongly disagree, 7: strongly agree) and for familiarity with blockchain technology the mean is 4.40 (SD=2.31; 11-point scale ranging from 0: not at all familiar, to 10: very familiar). Table 3.16 provides descriptive statistics.

Next, we analyze the quality of the measurement model, starting with evaluating internal consistency reliability, convergent as well as discriminant validity for the reflective constructs. For all these constructs, values for composite reliability (CR) and Cronbach's α are above the proposed cutoff value of 0.7 [smallest CR value TPR (.821); smallest Cronbach's α TPR (.719)], confirming internal consistency reliability. Concerning convergent validity, we assessed each construct's average variance extracted (AVE) and each indicator's outer loading. For the prior, all values were above the commonly applied threshold value of 0.5 (Hair, Ringle, and Sarstedt, 2011), for the latter, however, two items [TPE1 (.611), TPR2 (0.683) and TPR3 (.684)] had an outer loading below 0.7 (Hair et al., 2016) (Table 3). Following Hair et al. (2016), we examined whether the threshold values for AVE and internal consistency reliability can be reached by removing these items. Since the threshold values have already been met before, we decided to retain the items and proceed with the assessment of discriminant validity. The Fornell-Larcker criterion (Fornell and Larcker, 1981), the Heterotrait-Monotrait Ratio (HTMT), as well as the consideration of cross-loadings, were checked, all confirming sufficient discriminant validity. Table 3.16 summarizes the properties of the reflective measurement scales.

For the formative constructs, we analyze the variance inflation factor (VIF) of the formative indicators to assess the measurement models for collinearity between indicators. All VIF values were below 5 (highest value 1.181 for TBL1 and TBL2), indicating that no collinearity issues between the indicators are occurring. Formative indicator relevance and significance testing resulted in the decision to drop TBU1 (outer weight insignificant, and outer loading below 0.5). Last, we control for collinearity issues among predicting constructs. All VIF values are well below the cutoff value of 5 (Hair et al., 2016), providing evidence for not facing collinearity issues within our structural model.

Table 3.16: Properties of measurement scales. Diagonal values indicate the square root of AVE. * Denotes if HTMT confidence interval includes 1.

Construct	Mean	SD	Cron. α	CR	AVE	HTMT*	Correlations					
							ITR	**TBL**	**TBU**	**TPE**	**TPL**	**TPR**
ITR	3.157	1.312	.905	.940	.840	no	**.916**					
TBL	3.429	1.068	/	/	/	no	.559					
TBU	3.323	0.923	/	/	/	no	.233	.437				
TPE	3.157	0.822	.807	.874	.639	no	.309	.471	.424	**.799**		
TPL	3.152	0.925	.820	.881	.650	no	.544	.626	.473	.642	**.806**	
TPR	3.366	0.949	.719	.821	.535	no	.312	.505	.451	.614	.663	**.732**

To test the structural model, we employ PLS-SEM using SmartPLS 3.0 (Ringle, Wende, and Becker, 2019). Path significances were obtained by means of bootstrapping with 5,000 subsamples, no sign changes, bias-corrected and accelerated, and two-tailed hypotheses testing. Figure 3.13 shows the results for the PLS structural model.

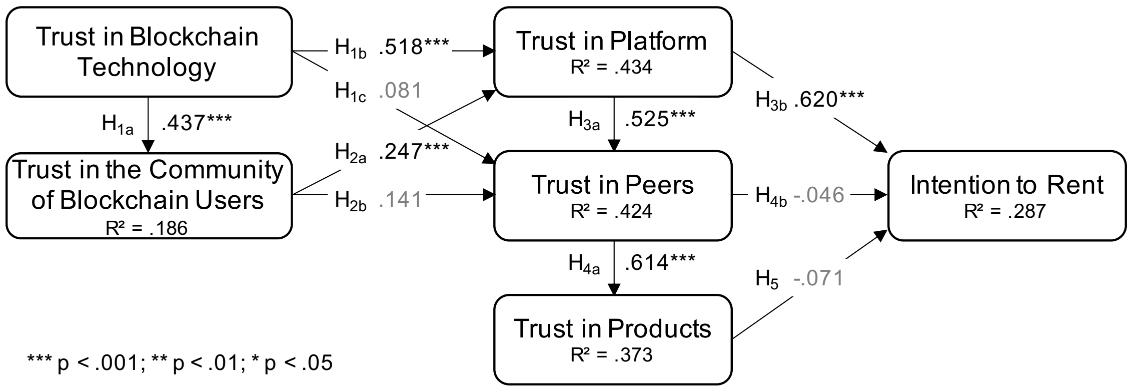

Figure 3.13: Results of PLS structural equation modeling (standardized path coefficients, R^2 adjusted)

As hypothesized, higher trust in blockchain technology has a positive influence on trust in the community of blockchain users (H_{1a}), as well as on trust in the service providing platform (H_{1b}). However, we do not find evidence for a significant relationship between trust in blockchain technology and trust in the providing peer, which is why hypothesis H_{1c} cannot be confirmed. In line with H_{2a}, higher trust in the community of blockchain users has a positive effect on trust in platform. The second hypothesis emanating from trust in the community of blockchain users, by contrast, is not significant, indicating no support for H_{2b}. Both hypotheses, which have their origin in trust in platform (H_{3a} and H_{3b}), can be confirmed, thereby suggesting that higher trust in platform leads to higher trust in peers and that it significantly increases the intention to rent a product. Following H_{4a}, we find evidence for higher trust in the providing peer leading to higher trust in their offered product. However, neither a positive effect of trust in peer on intention to rent (H_{4b}) nor of trust in product on intention to rent (H_5) can be confirmed—not confirming the proposed hypotheses.

Interestingly, only paths passing through trust in platform show a significant effect on the dependent variable intention to rent, revealing that trust in platform remains the only relevant predictor of intention to rent within the model. Overall, the model explains 28.7% (adj. R^2) of the variance in the intention to rent, with trust in platform being the only significant predictor ($f^2 = .259$; medium effect, classification following Henseler, Ringle, and Sinkovics, 2009). Concerning the other effect sizes, the effect of trust in blockchain on trust in platform (.389) and the effect of trust in peer on trust in product (.605) can be classified as large, whereas the effect of trust in blockchain on trust in the community of blockchain users (.236), as well as of trust in platform on trust in peer (.272), constitute medium-sized effects. The remaining significant relationship of trust in community of blockchain users on trust in platform shows a small effect size (.088). Table 3.17 summarizes effect sizes for all significant paths.

Table 3.17: Effect Sizes following Cohen (1988)

Independent Construct		Dependent Construct	Coef.	f^2	Effect Size
TBL	→	TPL	.518	.389	Large
TBL	→	TBU	.437	.236	Medium
TBU	→	TPL	.247	.088	Small
TPL	→	TPE	.525	.272	Medium
TPL	→	ITR	.620	.259	Medium
TPE	→	TPR	.614	.605	Large

Multi-Group Analysis

To assess the effects of control variables, we conduct a multi-group analysis (MGA). Thereby, we can estimate sub-group specific effects (Table 3.18). MGA yields seven significant group-specific differences. First, the relation of TPE and TPR is stronger for male than for female participants. Next, the older half of participants account for the effect of TBL on TPL, while this effect is insignificant for the younger half. Furthermore, the senior participants show a more prominent effect of TPL on ITR, and, somehow surprisingly, show a significant negative effect of TPR on ITR. The effect of TBL on TBU is stronger for participants less familiar with the blockchain and risk-seeking participants. Last, we find an effect of TBL on TPE—exclusively driven by participants with lower trust propensity.

Table 3.18: Results of MGA Analysis.

	Gender				**Age**				**Familiarity**				**Risk Prop.**				**Trust Prop.**			
	m	f			<23	≥23			<5	≥5			<7	≥7			<5	≥5		
	n:105	n:56	$\lvert\Delta\rvert$	Sig.	n:77	n:84	$\lvert\Delta\rvert$	Sig.	n:87	n:74	$\lvert\Delta\rvert$	Sig.	n:68	n:93	$\lvert\Delta\rvert$	Sig.	n:87	n:74	$\lvert\Delta\rvert$	Sig.
H_{1a}	.340	.456	.116	n.s.	.495	.422	.088	n.s.	**.550**	**.295**	**.282**	*	**.589**	**.313**	**.284**	*	.473	.367	.118	n.s.
H_{1b}	.486	.551	.065	n.s.	.601	.470	.129	n.s.	.597	.456	.146	n.s.	.533	.533	.002	n.s.	.444	.546	.103	n.s.
H_{1c}	.244	.024	.268	n.s.	.045	.175	.141	n.s.	-.032	.193	.226	n.s.	-.001	.101	.100	n.s.	**.240**	-.153	**.406**	*
H_{2a}	.359	.159	.200	n.s.	**.115**	**.341**	**.232**	*	.153	.351	.212	n.s.	.216	.262	.055	n.s.	.313	.184	.131	n.s.
H_{2b}	.157	.192	.035	n.s.	.161	.129	.027	n.s.	.181	.142	.034	n.s.	.271	.113	.144	n.s.	-.002	.270	.293	n.s.
H_{3a}	.419	.567	.148	n.s.	.571	.459	.123	n.s.	.633	.419	.213	n.s.	.479	.546	.059	n.s.	.530	.551	.016	n.s.
H_{3b}	.634	.596	.038	n.s.	**.403**	**.795**	**.387**	*	.563	.622	.040	n.s.	.690	.547	.134	n.s.	.597	.639	.041	n.s.
H_{4a}	**.718**	**.563**	**.155**	*	.590	.665	.087	n.s.	.632	.642	.011	n.s.	.623	.626	.012	n.s.	.670	.551	.126	n.s.
H_{4b}	-.067	-.038	.029	n.s.	-.073	-.011	.064	n.s.	-.029	-.072	.044	n.s.	-.166	.027	.193	n.s.	-.109	.010	.128	n.s.
H_5	-.024	-.094	.069	n.s.	**.265**	**-.314**	**.578**	**	.076	-.17	.228	n.s.	-.038	-.080	.049	n.s.	-.009	-.104	.108	n.s.

Qualitative Analysis

To better understand participants' answers in the survey, we re-invited them for qualitative feedback. Doing so, we asked each participant to describe in their own words, how the blockchain would affect their perceptions in the outlined scenario. We received 192 answers, which we classified into first, a positive or negative assessment, and second the six categories depicted in Figure 3.14. These categories were derived by initial screening of all responses individually, then discussed, refined, and, finally, applied by two researchers independently. With an average Cohen's Kappa score of .632 across all categories, we achieve a substantial agreement among our raters (Landis and Koch, 1977). Among the answers, stating to perceive an effect (161 total), 39.75% name Security aspects (79.69% positive), 34.16% Trustworthiness (90.91% positive), 10.56% Transparency (all positive), 4.35% Reliability (85.71% positive), and 3.73% Privacy (50% positive). 7,45% state to have not enough knowledge to evaluate a blockchain effect.

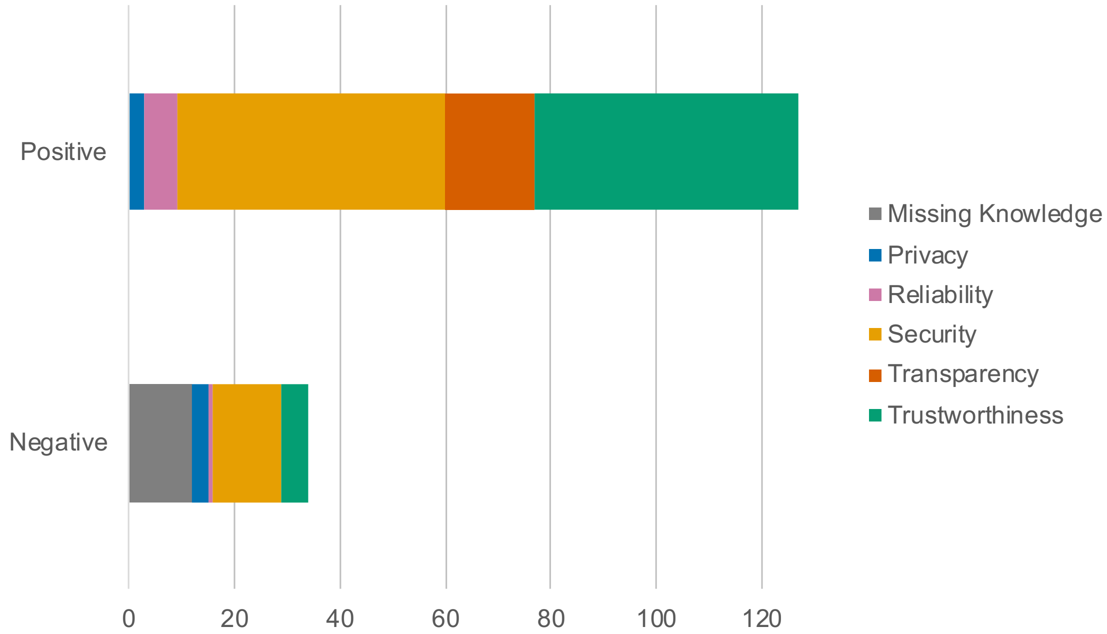

Figure 3.14: Categorization of participant answers. Categorization was non-exclusive (i.e., each answer can be assigned to multiple categories)

3.3.6 Discussion

We conducted an online survey to investigate how the application of blockchain technology in a P2P sharing scenario influences trusting beliefs. While previous research studies the blockchain mainly from a Bitcoin perspective (Auinger and Riedl, 2018; Sas and Khairuddin, 2015; Ahangama and Poo, 2016; Zarifis et al., 2015; Connolly and Kick, 2015; Connolly and Kick, 2015; Connolly and Kick, 2015), we consider the blockchain from a more general perspective as a technological foundation of a sharing platform. To the best of our knowledge, it represents the first study to provide reliable survey-based evidence with a sufficient sample size about the perception of such platforms. By assessing the perceptions of a blockchain-enabled platform, we enable a better understanding of how users evaluate potential transactions and how they are guided by their trust in three substantial targets of trust—peer, platform, and product. Our study contributes to theory and practice by showcasing how established trust relationships are influenced by the application of blockchain technology and by suggesting means how platform providers shall best answer to these influences. Interestingly, we do not find support for four of our hypotheses, from which H_{4b} and H_5 embody well-established relations within the P2P sharing economy and trust literature (Connolly and Kick, 2015; Huurne et al., 2017). A potential explanation for this could be that as soon as a platform ecosystem is based on a trusted and (assuming trusted interfaces) potentially "trust-free" technology, other trust relationships are diminishing in importance, so that trust in the individual transaction partner constitutes no longer an important predictor for the ultimate decision to enter a transaction on the platform. Trust in the facilitating platform run on blockchain technology consequently increases in importance. In this context, users seem to especially value blockchain's security-, trustworthiness-, and transparency-related aspects: *"I would have a higher trust in the sharing platform since I do not have to trust the other users anymore"* [Respondent 107, male, 26].

Thus, we experience a shift from trust in individual transaction partners to trust in platforms. Therefore, the term "trust-free systems" (Greiner and Wang, 2015) with which the blockchain is frequently associated, fits in so far as trust in the individual seems no longer to be a great matter of concern. Before such a platform landscape can be successfully implemented, trust in the overall blockchain technology must be ensured. In line with our results, there is a substantial effect of trust in blockchain technology on trust in platform. As a consequence, platforms need to build trust in the blockchain technology itself. Interestingly, those effects remain stable, though smaller, even when controlling for experience with the blockchain technology itself, contrasting previous literature describing it as an essential prerequisite (Greiner and Wang, 2015). A possible explanation for this is the composition of our participant pool of IS student Millennials—the explicit target group of P2P sharing services and familiar with technological novelties (Greiner and Wang, 2015; Greiner and Wang, 2015; Greiner and Wang, 2015; PwC, 2015; Akbar, Mai, and Hoffmann, 2016). Even though (and in line with the quantitative data of our total sample) participants state that the blockchain *"[. . .] does not affect the credibility of the offering users"* [Respondent 103, female, 19 years], we find a trust-enhancing effect of trust in blockchain technology for the subgroup with a lower trusting propensity.

Summarizing, platform managers may consider leveraging the blockchain technology to increase the level of trust that users place in the platform. This can particularly affect novel platforms that lack an established user base. Especially here, reputation mechanisms cannot attain their full potential, as they are often subject to the "cold start" problem (Akbar, Mai, and Hoffmann, 2016). This refers to the initial state of either the platform user (or the platform itself), in which few or none transactions are completed, and no reputation can be propagated by common reputation mechanisms (e.g., star ratings, text reviews, profile images). Fostering first transactions would benefit both sides of P2P platform users since it supports them realizing first transactions and build a reputation on the platform. Platform providers should not entirely omit reputation systems, since users may *"still need confirmed reviews by other peers about the 'sharing partner' [. . .] to trust the other person"* [Respondent 182, female, 21 years]. The combination of blockchain as the underlying technology of a platform with reputation systems could be a viable strategy for platforms for which the blockchain *"will not affect the reliability of the physical products"* [Respondent 100, male, 29 years].

On the other hand, blockchain technology may help established platforms as well. As soon as common reputation mechanisms are devalued by, for instance, inflationary positive assessments (Akbar, Mai, and Hoffmann, 2016; Akbar, Mai, and Hoffmann, 2016; Akbar, Mai, and Hoffmann, 2016; Akbar, Mai, and Hoffmann, 2016; Akbar, Mai, and Hoffmann, 2016; Bridges and Vásquez, 2018), or a discriminatory use of these (Edelman and Luca, 2014; Edelman, Luca, and Svirsky, 2017), trust in the platform and the assurance of further transactions (and thereby the platform's continued existence) could be supported by an underlying blockchain technology.

3.3.7 Limitations & Future Research

Like any study, the present paper faces limitations. First, the decision to enter a transaction on a P2P sharing platform may differ from the statements made within a scenario-based online survey—with potential external influences. While laboratory studies might create a higher level of internal validity, field experiments might create a higher level of external validity. Next, our sample of undergraduate Millennials lessens the generalizability of our effects. Although this group is particularly relevant for P2P sharing platforms, a broader sample should be considered to derive more general implications. Further, as our research model shows a number of unsupported hypotheses, effects of demographic and trait variables, and a certain amount of unexplained variance, this indicates potential for further influencing factors to be considered. Future research may follow a broader qualitative approach to identify further influencing factors. Last, longitudinal studies are needed to clarify the effects of diminishing trust-enhancing effects for users with higher familiarity with blockchain. The question arises if, in the long-term, *"[h]aving information about how Blockchain is working would increase my trust"* [Respondent 30, female, 23 years] or *"Blockchain is just a hype word"* [Respondent 82, female, 26 years]. It this sense, we recommend putting more research efforts into the promising and highly relevant field of trust in blockchain and distributed ledger technology as well as the corresponding antecedents. Especially, we recommend to further investigate real-world use-cases and platforms, which—admittedly and despite the hype during the last years—still lack significant traction and success.

3.4 How do Tax Compliance Labels Impact Sharing Platform Consumers? An Empirical Study on the Interplay of Trust, Moral, and Intention to Book

Following the analysis of how the technological layer of a platform itself affects its users, this chapter considers P2P platforms from a societal perspective. The main focus is on the perception of users' tax behavior. Certain platform-based business models facilitate tax evasion as tax authorities typically lack information to monitor the income generated by providers on these platforms. Moreover, it is not clear whether tax compliance of the respective transaction partner constitutes a value for consumers at all. Therefore, this study investigates the role of tax compliance for platform users by employing an online experiment. The results show that consumers perceive providers' tax compliance and regard it as a trust-enhancing signal for which they are also willing to pay a premium. The results also show how consumers' moral norms moderate both the trust-building effect and the subsequent transaction intention. Based on the results, policymakers should actively engage in cooperation with platform operators to ensure tax compliance among users and a level playing field in the platform economy.

David Dann, Raphael Müller, Ann-Catherin Werner, Alexander Mädche & Christoph Spengel[12]

3.4.1 Introduction

Over the last two decades, we have seen a tremendous digitalization of our economy and society. In particular, digital platforms play an important role in this ongoing process and have grown in popularity and size. Today, they are an integral part of the economy (Mittendorf, Berente, and Holten, 2019; Zimmermann et al., 2018; European Commission, 2016).

With that development, we have also seen the birth and rise of the so-called "sharing economy" (Sundararajan, 2016; Teubner and Hawlitschek, 2018), in which idle resources are efficiently shared among different user groups. Peer-to-Peer (P2P) platforms are considered particularly interesting in terms of user uptake, revenues, and firm value (Zijm et al., 2019). These platforms facilitate the exchange of goods and services between mostly private providers and consumers in various segments (e.g., accommodation, retail, mobility, Resnick and Zeckhauser 2002; Ma, Neeraj, and Naaman 2017; Teubner and Flath 2015). The worldwide gross volume generated by the platform-driven gig and sharing economy is estimated to grow to USD 455 billion by 2023 doubling the gross volume of USD 204 billion in 2018 (Mastercard and Kaiser Associates, 2019). One of these key sectors is P2P accommodation sharing (European Commission, 2016). Airbnb, the most prominent player within this domain, provides listings from over 220 countries and regions and estimates that there have been over 500 million guest arrivals at listings from their platform since it was founded in 2008.[13] Depending on the platform's revenue

[12] By this thesis's submission date, this study was under review at the *Business & Information Systems Engineering* journal.

[13] https://news.airbnb.com/fast-facts/

model, platform operators are estimated to receive up to 15% of the revenues (Vaughan and Daverio, 2016).

Besides their increasing economic relevance, platform businesses, however, are said to cause several problems for the economy and society in general. For the prominent example of P2P accommodation sharing, the most pressing concerns include local side effects such as over-touristification (Oskam and Boswijk, 2016), ever-increasing rent prices (Gurran and Phibbs, 2017), and illegal hospitality operations (Schäfer and Braun, 2016). Furthermore, ensuring an adequate taxation of the sharing economy's booming revenues is identified as one of the major regulatory challenges that policymakers on national and international level are concerned with. In the US, for instance, less than 25% of all Airbnb providers meet local tax obligations (Bibler, Teltser, and Tremblay, 2019). For the German market, the annual revenues generated via Airbnb amount to approximately €700 million and would generate income tax revenues of more than €100 million (Bräutigam, Ludwig, and Spengel, 2019). In light of the volume of tax revenues at stake, ensuring tax compliance is one of the most salient public interests in the platform economy (Frenken et al., 2019). Hereby, tax compliance describes the decision of the income earning individuals to declare their income truthfully and to pay the respective amount of taxes on that income, in accordance with the applicable tax laws (Slemrod, 2018; Mascagni, 2018). This raises questions on the adequate implementation of both indirect (value-added) and direct (income) taxation systems (European Parliament, 2017). Recently, the OECD stated that improving self-reporting by individual providers (e.g., Airbnb hosts) is one of the main policy concerns and called for exploring different design options to ensure that taxable income is truthfully reported (OECD, 2019).

On the other hand, the success of the P2P sharing platforms depends on the typical characteristics of two-sided markets. The one user group, providers (e.g., hosts), benefits from the existence and activity of the other, consumers (e.g., guests)—and vice versa (McAfee A and Brynjolfsson, 2017). In this context, research has shown that platform users' mutual trust represents one of, if not the most important, prerequisite for users on P2P platforms (Gebbia, 2016; Hawlitschek, Teubner, and Weinhardt, 2016), and thereby, the platforms overall continued existence (Hodapp, Hawlitschek, and Kramer, 2019). If providers are, however, suspected to engage in tax evasion by non-reporting their income realized via the transactions on the platform, they may be threatened with mistrust from prospective customers. In the domain of P2P platforms, arising mistrust, in turn, typically also raises fear of fraud, misconduct, or even harassment (Abramova, Krasnova, and Tan, 2017; Krasnova et al., 2009). To address trust-related aspects in general, platform operators implement reputation mechanisms within their platform design to ensure and propose a high level of service quality. One of these mechanisms are quality labels. Visual labels (often referred to as "badges") aim to propagate certain qualifications or service quality standards (Hesse et al., 2020; Teubner and Hawlitschek, 2018; Dann, Teubner, and Weinhardt, 2019). Studies document that the information inherent to these labels translates into increased levels of trust, willingness to pay more for offers from such providers (Abramova, Krasnova, and Tan, 2017; Liang et al., 2017), and transaction numbers (Ke, 2017b). While tax-relevant behavior of providers remains unobservable for consumers, the important question here is whether providers can benefit from indicating their tax compliance with regard to their platform-based income.

Against this backdrop, we provide first answers to this question by examining whether a quality label that signals tax compliance affects consumers' evaluations of the respective provider's trustworthiness and, in turn, their transaction intentions (i.e., to book) at such a provider. Specifically, we raise the following research question:

RQ1: *How does the presence of a tax compliance label affect consumers' trust towards and, in turn, their intentions to book at the tax-compliant provider?*

The extent to which consumers respond to the label likely depends on the perceived relevance of tax compliance for the consumers. Personal values and moral beliefs are known to be important determinants for individuals' behavior (Bergquist, Nilsson, and Schultz, 2019) and to influence their economic decisions (Frey and Torgler, 2007; Antonetti and Anesa, 2017). Given that tax evasion is a controversial topic due to its adverse effects on public budgets, we examine the role of moral norms on consumers' evaluation of the tax compliance label to understand the mechanisms through which a tax compliance label influences consumers' reactions. Therefore, we also raise the research question:

RQ2: *How do individual moral norms moderate the effect of tax compliance labels?*

It is important to note that the effectiveness of a tax compliance label critically hinges on how such labels are awarded. Only if the platform can assure beyond doubt that a certain provider does in fact pay taxes on their platform income, the label can be assumed to be credible and hence have an effect. The platform operator, therefore, needs to share information with the tax authority and displays the tax compliance label on an individual provider's profile once it receives information that the provider has correctly declared his platform-related income and paid the respective tax liability. Airbnb already shares some information with tax authorities and has entered co-operations with several local tax authorities and municipalities to collect occupancy taxes (Airbnb, 2020b; Beretta, 2017).

In our paper, we develop a research model tying together the effects of a tax compliance label and consumers' booking intention. Our analysis is based on the theoretical lens of signaling theory (Spence, 1973). We evaluate our research model by means of an online experiment (n=286) in which participants take the role of consumers and evaluate a set of available listings and, implicitly, the associated providers. Furthermore, we provide qualitative insights into consumers' perceptions of tax-compliant providers based on open-ended written responses.

Overall, our paper makes two main contributions. First, we extend existing knowledge about consumers' transaction intentions on sharing economy platforms. We show that consumers do indeed reflect on providers' tax behavior, finding that a visual tax compliance label positively influences consumers' trust in a provider. Moreover, consumers' moral norms take a moderating role in both the trust-fostering effect of the tax compliance label and the positive effect of trust on consumers' willingness to enter a transaction. Prior literature on the role of tax compliance for consumer behavior reports mixed results on whether corporations face reputational costs for their tax planning (i.e., legal and "grey area" measures to reduce the tax liability; Slemrod, 2018) (Gallemore, Maydew, and Thornock, 2014; Hardeck and Hertl, 2014; Hoopes, Robinson, and Slemrod, 2018). To the best of our knowledge, this study represents the first to examine consumers' reaction to tax behavior of P2P accommodation sharing users. Second, our results provide several practical implications for platform users, operators and policymakers. Consumers are not only more willing to enter transactions with providers that hold the tax compliance label, they also are willing to pay a price premium. This indicates a proverbial "win-win-win" situation for platform users, operators, and policymakers.

3.4.2 Conceptual Background and Related Work

Taxation in the Platform Economy

The taxation of the digital economy is under large public scrutiny (OECD, 2015). The profits of the platform operator (e.g., Airnbnb, Uber) are subject to corporate income tax in the country of residence of the business (i.e., the place of legal seat or management Endres and Spengel, 2015; OECD, 2017). However, the key challenge regarding the sharing economy is to ensure the taxation of the individual providers, who generate income on the platform. The taxation of income resulting from platform-based activities follows the same rules that have been established to tax the income of individuals and businesses in the traditional economy. The income realized by the provider typically constitutes taxable income and qualifies either as private income or as business income depending on the professional capacity with which the activities are carried out. In case of P2P accommodation sharing, the income from letting apartments or rooms is generally treated as rental income from immovable property which is taxed at the personal income tax rate. This means that the providers are responsible for filing and reporting the income and related expenses in their tax returns according to existing tax regulations (Kußmaul and Kloster, 2016; Beretta, 2017).[14] From a legal perspective, the tax treatment of income realized by providers is, therefore, unambiguously regulated by existing tax laws.

For the German market, Bräutigam, Ludwig, and Spengel (2019) examine the activities on Airbnb. Using publicly available data, they estimate an annual turnover realized via transactions on Airbnb of €700 million in 2018 and, with that, an income tax revenue of roughly €114 million. However, tax authorities typically face difficulties in enforcing existing tax provisions for the entire platform economy. In particular, tax authorities lack information about the numerous online transactions between (mostly private) providers and consumers and have to rely on the self-reported information provided in tax returns (European Commission, 2016; Elliot, 2018). Furthermore, the declared personal income in the providers' tax returns is suspected to deviate from their actual income (Bräutigam, Ludwig, and Spengel, 2019). The deviations mainly occur for two reasons.

First, many providers are only occasionally letting their apartments or rooms and may not be aware of the tax implications of their activities (Grlica, 2017). According to a survey among providers in the UK, 54% of respondents stated that they are not required to pay taxes on their sharing economy income (Rahim et al., 2017). Another

[14] In addition to income taxes, most jurisdictions also levy consumption taxes (e.g., the value added tax, VAT, in the European Union) on the monetary consideration paid by the consumer to the provider for the provision of goods and services. If the annual turnover of the provider exceeds a certain threshold, the provider is obliged to register with national tax authorities and to account for VAT (Beretta, 2018).

13% of respondents did not know about their tax liability. Further, the determination of taxable income is not trivial and requires detailed documentation of income and related expenses. Airbnb and Uber provide some general information on potential tax obligations but no specific guidance for providers (Airbnb, 2020c; Uber, 2020).

Second, some providers may deliberately evade taxes by reporting low or no earned income from renting activities, which renders the tax enforcement even more burdensome. Tax evasion refers to all illegal and intentional actions by individuals to minimize their tax obligations (Alm and Torgler, 2011). P2P platforms arguably facilitate tax evasion as tax authorities lack resources and effective mechanisms for monitoring providers. Alm, Deskins, and McKee (2009) show that self-reporting and low detection probability induce higher non-compliance of taxpayers. Besides some anecdotal evidence covered by the media (Ramthun, 2018; Fricke and Linnemann, 2018), empirical evidence on the extent of tax evasion by providers in the platform economy is scarce. Two recent studies provide strong, but indirect evidence that Airbnb providers do not report their full income in the absence of additional compliance mechanisms (Bibler, Teltser, and Tremblay, 2019; Wilking, 2019). And indeed, the estimated losses in tax revenues resulting from the discrepancy between declared and actual income are substantial. For the US, Bibler, Teltser, and Tremblay (2019) conclude that less than 25% of Airbnb providers comply with local tax obligations. Non-compliant providers gain an unfair advantage over honest providers as they can demand lower prices and, thereby, distort competition with traditional providers such as the traditional hotel industry (OECD, 2019). More importantly, tax evasion challenges public budgets—a context, which can lead to moral reflections regarding the individual responsibility towards a society.

Moral Norms

In the tax compliance literature, scholars argue that moral norms are a central explanation of why most people pay their taxes even though detection probabilities and fines are rather low (Torgler et al., 2008; Pickhardt and Prinz, 2014). In fact, personal moral norms with respect to paying taxes are strongly correlated with the individual decision to comply with tax regulations (Wenzel, 2004; Cummings et al., 2009; Jimenez and Iyer, 2016; Fochmann, Müller, and Overesch, 2018).

People define their moral standards based on personal values and beliefs. The construct of "personal moral norms" is closely related to personal attitudes (i.e., the evaluation of the outcome of a particular behavior). Botetzagias, Dima, and Malesios (2015), for instance show this in the context of recycling intentions. Personal norms are strongly influenced by social norms of the relevant reference group, which may be personally adopted and internalized (Schwartz, 1977; Luttmer and Singhal, 2014; Hofmann, Hoelzl, and Kirchler, 2008). In line with this, Frey and Torgler (2007) conclude that the individual tax morale depends on the pro-social behavior of other taxpayers.

Prior research suggests consumers take moral considerations into account when interacting with companies. Hoopes, Robinson, and Slemrod (2018) find that consumers' sentiment for brands of domestic firms declines after the firms' actual tax payments are publicly disclosed by the government. Similarly, consumers evaluate firms' reputation and ethicality more negatively if these firms are associated with strategic tax reduction (Hardeck and Hertl, 2014; Antonetti and Anesa, 2017). The study of Hardeck and Hertl

(2014) shows that the reputation of tax planning firms is significantly lower among consumers who consider strategies that reduce the tax burden as unethical. The authors conclude that moral beliefs are an important criterion for consumers when evaluating firms' observable corporate tax behavior. Yet, the overall effect of moral norms on actual purchase decisions is less clear. According to a recent survey among US consumers, participants indicate higher willingness to purchase from firms that did not engage in any form of corporate tax planning (Asay et al., 2018). In experimental studies, participants penalize tax avoiding firms with a reduced willingness to pay for their products and overall lower purchase intentions (Hardeck and Hertl, 2014; Antonetti and Anesa, 2017). In contrast, Gallemore, Maydew, and Thornock (2014) do not observe changes in sales or advertising expenses of US firms that have been revealed to engage in tax planning. Still, the evidence implies that consumers are aware of morality aspects with respect to tax compliance.

Labels, Reputation, and Trust

Demonstrating trustworthiness is essential for successful participation on P2P platforms (Tussyadiah and Park, 2018). Studies have shown trust in a prospective transaction partner is a crucial factor and that a lack of trust is likely to hinder the realization of any transaction (Hawlitschek, Teubner, and Gimpel, 2016). Unsurprisingly, major platforms explicitly state to design for trust (Gebbia, 2016) and give users the opportunity to establish their trustworthiness and to establish a reputation on the platform. This reputation is of vital importance for providers as they have to market themselves via the platform to generate demand (Tussyadiah, 2016b). To this end, platform operators implement various artifacts such as star ratings or text review systems (Hesse et al., 2020; Dann et al., 2020b).

Among the most successful trust-building artifacts are platform-specific visual labels. Typically, these labels are granted by platforms themselves and are intended to certify a user's superiority in terms of one or more value dimensions. This separating component of superiority may relate to different aspects. It may indicate that the user has demonstrated a particularly high level of service quality in the past (e.g., consistently high evaluations from transaction partners), has achieved a particular proficiency or achievement on the platform (e.g., long-term membership), or has been verified in some form (e.g., by means of an ID card). Indeed, scholars show that consumers are willing to pay more for offers from such providers (Abramova, Krasnova, and Tan, 2017; Liang et al., 2017). On Airbnb, for instance, the Superhost label attests that a provider fulfils excellent standards in the dimensions communication, commitment, guest satisfaction, and experience (Airbnb, 2014b). The effectiveness of such labels is undisputed. Users state to perceive providers with the Superhost label as high-quality and are willing to pay a price premium (Liang et al., 2017). Further empirical evidence reflects this pattern where quality labels appear to be a significant driver of prices (Teubner et al., 2016; Wang and Nicolau, 2017; Kakar et al., 2018) and the amount of realized transactions (Ke, 2017b). Given that no official nor otherwise visible verification of the tax-compliant behavior is available, consumers are not able to differentiate tax-compliant (i.e., honest) providers from non-compliant providers. Since, at the same time, individual tax evasion is perceived as immoral behavior (Kirchler, Maciejovsky, and Schneider, 2003; Frey and

Torgler, 2007), a non-compliant tax behavior on P2P sharing platforms poses a risk to their general reputation—and the platform economy as a whole.

Signaling Theory

To provide a theoretical frame for the role of tax compliance labels in our study, we draw on signaling theory (Spence, 1973). The theory assumes markets with information asymmetry, for instance, between job seekers and employers or online vendors and customers. According to signaling theory, the more informed side (i.e., job seekers, sellers) can use signaling (or *signals*) to demonstrate their otherwise unobservable quality (e.g., talent, skill, intelligence, product quality; Basoglu and Hess, 2014). One of the fundamental principles of signals is that they are inherently costly. The individual signaling costs depend on the underlying trait that the signal is intended to represent, that is, higher quality is associated with lower costs. For instance, wealth is clearly signaled by a $250K sports car or a $75K wristwatch since these signals are prohibitively expensive for non-wealthy individuals. Moreover in biology, it is assumed that gazelles' stotting behavior (i.e., jumping into the air, lifting all four feet off the ground simultaneously) is used to signal physical fitness to predators (which, in turn, target other, non-stotting gazelles). Another example is the signaling of high product quality through the provision of warranties. For sellers of low-quality products, this strategy will—ceteris paribus—be much more costly as their products will fail more often and cause warranty claims. This cost differentiation for high- and low-quality "sellers" causes a separating equilibrium in which it is only worthwhile for high-quality sellers to acquire the costly signal. The signal itself therefore becomes a separating factor.

Within the context of platforms and accommodation sharing in particular, similar informational asymmetries between consumers and providers exist. This aspect becomes particularly precarious considering that (1) in almost every transaction on P2P platforms, both sides interact with each other for the first time (Teubner, 2018), and (2) most offers are run by private individuals rather than corporate hospitality providers (Ke, 2017b). In this sense, tax compliance labels constitute a signal of honesty, integrity, and a sincere interest in societal well-being and the common good through paying taxes (as credibly documented by the signal). The underlying premise here is that for honest and sincere providers, paying taxes represents a matter of course. For them, in the sense of the theory, providing this signal does not incur any additional costs since they would pay taxes in any case. For dishonest providers who would rather refrain from paying taxes on their rental revenues, in contrast, providing the signal (tax compliance label) comes at a much higher cost, that is, the cost of actually paying the taxes.

Related Work

With respect to the platform economy, recent tax research has mainly focused on quantifying the extent of non-compliance on P2P platforms (Bibler, Teltser, and Tremblay, 2019; Wilking, 2019). While non-compliance seems to be widespread among individual providers on P2P platforms (Ramthun, 2018), it is unclear whether tax compliance of providers constitutes a relevant factor for platform consumers and influences their decision to enter transactions. Previous studies mainly examine consumers' reactions to certain tax behavior by companies (e.g., Hoopes, Robinson, and Slemrod 2018; Asay et al. 2018; Hardeck, Harden, and Upton 2019) on consumer reactions to corporate tax planning). In this context, only Hardeck and Hertl (2014) investigate the role of individual norms to frame the perception of corporate tax strategies. In contrast to legal tax reduction strategies, tax evasion constitutes an illegal infringement of tax law. Since consumers' acceptance of illegal tax evasion by other individuals likely differs from their attitude toward legal tax planning (Kirchler, Maciejovsky, and Schneider, 2003; Kasper et al., 2018), insights on consumer reactions from prior studies might not be directly transferable to the platform economy. Hence, the examination of, so to speak, individual's tax strategies on platforms remain unconsidered so far. Platform economy literature shows that visual labels constitute an effective means to establish trust and to boost individuals' reputation (Liang et al., 2017; Teubner et al., 2016; Wang and Nicolau, 2017; Kakar et al., 2018; Ke, 2017b). The consideration of labels as a signal for tax compliance, however, has not been considered in the literature so far. Thereby, bringing both the platform economy and tax perspectives together, our interdisciplinary approach addresses a clear research gap (see Table 3.19). We examine tax evasion on P2P platforms by identifying causal effects of the interplay of visual tax compliance labels, moral norms, trust, and transaction intention.

Table 3.19: Related Literature

	Context				**Perspective**	
Publication	Tax	Labels	Moral Norms	Trust/ Reputation	Indivi-dual	Corpo-rate
Kirchler, Maciejovsky, and Schneider (2003)	×			×	×	
Wenzel (2004)	×		×		×	
Frey and Torgler (2007)	×		×		×	
Hofmann, Hoelzl, and Kirchler (2008)	×		×		×	
Torgler et al. (2008)	×		×		×	
Cummings et al. (2009)	×		×		×	
Hardeck and Hertl (2014)	×		×	×		×
Pickhardt and Prinz (2014)	×		×		×	
Gallemore, Maydew, and Thornock (2014)	×			×		×
Jimenez and Iyer (2016)	×		×		×	
Antonetti and Anesa (2017)	×			×		×
Asay et al. (2018)	×			×		×
Fochmann, Müller, and Overesch (2018)	×		×		×	
Hoopes, Robinson, and Slemrod (2018)	×			×		×
Kasper et al. (2018)	×			×	×	
Bibler, Teltser, and Tremblay (2019)	×				×	
Wilking (2019)	×				×	
Hawlitschek, Teubner, and Gimpel (2016)		×			×	
Teubner et al. (2016)		×		×	×	
Tussyadiah (2016b)		×			×	
Abramova, Krasnova, and Tan (2017)		×		×		
Ke (2017b)		×			×	
Liang et al. (2017)		×			×	
Neumann and Gutt (2017)		×			×	
Scheiber (2017)		×				
Teubner, Hawlitschek, and Dann (2017)		×			×	
Wang and Nicolau (2017)		×			×	
Xie and Zhenxing (2017)		×			×	
Kakar et al. (2018)		×			×	
Tussyadiah and Park (2018)		×		×	×	
Ert and Fleischer (2019)		×		×	×	
This Study	×	×	×	×	×	

3.4.3 Hypotheses Development

To understand how signals of tax compliance manifest themselves in consumers' perceptions of providers and how this perception ultimately affects their willingness to enter into a transaction with them, our research model (Figure 3.15) regards the dimensions of trust and moral norms. We approximate the transaction intention by means of customers' intention to book an offer on a P2P accommodation sharing platform. Since the positive association of trust and intention to book has already been demonstrated conclusively by various studies (e.g., Teubner and Hawlitschek 2018; Teubner et al. 2014; Hawlitschek, Teubner, and Gimpel 2016; Liang, Choi, and Joppe 2018b; Mittendorf 2017), we consider this positive relationship as given. We develop our hypotheses in the following.

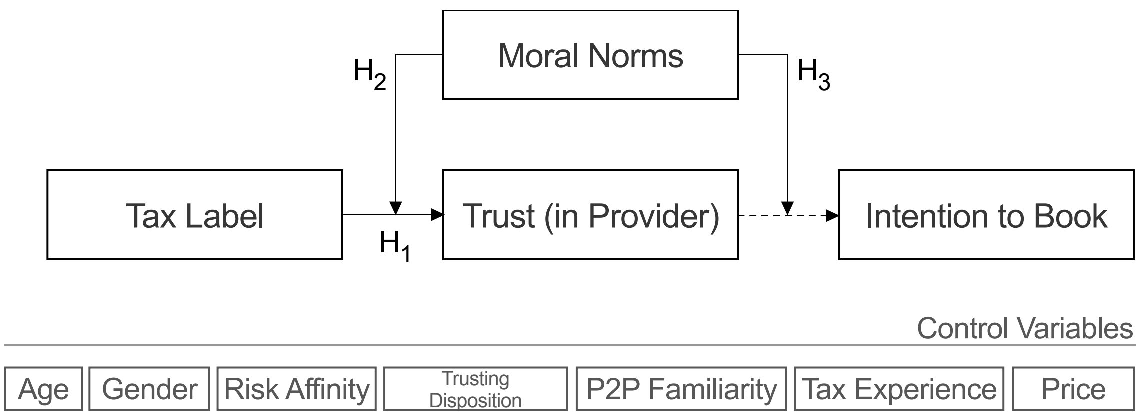

Figure 3.15: Research Model

The Influence of Tax Compliance Label on Trust (H_1)

Existing literature shows that labels imply quality (Liang et al., 2017) and can establish trust (Teubner and Hawlitschek, 2018). Platform users even seem to be well aware of the effectiveness of these labels and claim to use them strategically (Neumann and Gutt, 2017; Liang et al., 2017). Signaling theory in the context of tax compliance hence means that labels are a necessary means to establish a separating equilibrium in which only the actual tax-compliant providers will bear the cost of acquiring the label. Hence, we hypothesize that a label for tax-compliant behavior constitutes a signal to create a separating equilibrium that positively influences the perception of how trustworthy a provider is. Formally, our hypothesis states:

H_1: *The presence of a tax compliance label has a positive effect on consumers' trust in the provider.*

The Moderating Role of Moral Norms (H_2 and H_3)

Prior research further suggests that consumers react to corporate behavior contingent on the perceived congruence between a firm's character and their own character (Sen and Bhattacharya, 2001; Hardeck and Hertl, 2014). In the context of tax behavior, tax morale constitutes an important determinant of the level of congruence. For instance, consumers' individual moral norms seem to moderate the effect of corporate tax planning on corporate reputation (Hardeck and Hertl, 2014). Moreover, the evaluation of firms' tax behavior by consumers is strongly linked to their personal attitudes towards taxation (Antonetti and Anesa, 2017). Similarly, information about a person's tax compliance does influence the overall perception of that person. Confronted with different types of tax behavior (tax avoidance, tax flight and tax evasion), people consider tax evasion immoral and unfair toward society (Kirchler, Maciejovsky, and Schneider, 2003). Kasper et al. (2018) document that people attribute positive characteristics to honest taxpayers whereas tax evaders are judged least favorable and described as "aggressive" and "uncooperative".

In the platform economy, where non-compliance is equivalent to tax evasion, we therefore expect similar observations. Specifically, we expect that consumers that consider tax compliance as a moral obligation towards society perceive strong congruence with providers holding a signal of tax-compliant behavior:

H_2: *The effect of the tax compliance label on trust in the provider is stronger if tax compliance is in line with consumers' moral norms.*

Apart from reputational aspects, moral norms also frame actual behavior. Studies on pro-environmental behavior show that norms may help to address environmental problems (see, e.g., Bergquist, Nilsson, and Schultz, 2019). Beyond pro-environmental behavior, moral norms also affect mere economic decisions. A large body of literature confirms the positive effect of tax morale, that is, the perceived moral obligation to pay taxes, on personal tax compliance decisions (Wenzel, 2004; Alm and Torgler, 2006; Frey and Torgler, 2007). In addition, moral norms seem to moderate the effect of other determinants on tax compliance. Wenzel (2004), for instance, shows that the threat of monetary sanctions and legal consequences only have a deterrent effect on tax evasion if taxpayers consider tax evasion to be a minor offense (i.e., if they have weak personal norms regarding tax compliance).

Besides personal tax behavior, moral norms also moderate the willingness of consumers to enter into economic transactions with firms (Antonetti and Anesa, 2017). Participants with a negative attitude toward legal tax planning exhibit both lower purchase intentions and a reduced willingness to pay for a product of a firm that was associated with corporate tax planning (Hardeck and Hertl, 2014). These findings are in line with Asay et al. (2018)—participants that are aware of specific cases of negative corporate tax practices claim to have declined purchasing from those firms due to their tax behavior.

To summarize, this implies that consumers prefer providers whose presumably observable behavior (i.e., tax compliance) is in line with their moral norms and what they think is the right thing to do (Klöckner, 2013). We hypothesize:

H_3: *The effect of trust in the provider on intention to book is stronger if tax compliance is in line with consumers' moral norms.*

3.4.4 Method

We evaluate our research model by means of an scenario-based online experiment. Participants take the role of consumers and consider a set of listings from different providers. Employing a treatment-based experiment allows us to have a high degree of control and, at the same, allows for causal claims on the effects of the exogenous treatment variables (i.e., the presence of tax compliance labels) (Friedman and Cassar, 2004).

Scenario and Treatment Design

Participants face the following scenario. They are looking for a place to stay in a foreign city for two nights for themselves and a friend. For this trip, they are looking for a suitable accommodation on an P2P sharing platform. Their friend has already pre-selected one of five available listings of different configuration (Table 3.20), and they are now in charge of evaluating this pre-selected listing in terms of how likely they would be to actually book it. The treatment design manipulates the configuration of the pre-selected accommodation such that the listing either has a tax compliance label or not (binary treatment design). Each participant is either in one or the other treatment condition (between-subjects design). To ensure a high degree of comparability between treatments, two out of the five listings have the tax compliance label, while the other three do not. Depending on the treatment condition, the pre-selected listing is either one of the two with the label, or one of the three without.

Stimulus Material

To create an engaging scenario and to mimic an actual search/booking process as close as possible, we visually align our stimulus material with that of popular accommodation sharing platforms such as Airbnb (see Figure 3.16; right). After being welcomed and having read the scenario description, participants are forwarded to the overview page, showing the five listings including their friend's pre-selection. The rating of each listing is randomly set to either 4.5 or 5 stars and the number of ratings is randomly chosen from the range of 14 and 17.[15] In order to prevent any inferences about merits of the individual listings (e.g., information about the location), the titles as well as the pictures and the markers on the overview map are blurred.

Tax Compliance Label Since tax compliance labels are not (yet) used by any major platform, we newly design such a label (Figure 3.16; left). Given the scenario is set in Germany and also the sample is recruited from Germany, the label uses typical design elements associated with German Federal Ministries (i.e., the federal eagle). Regarding color, the design is mainly kept in blue tones, following Sundar and Kellaris' (2016) emphasis of color symbolism. During the experiment, participants were able to mouse-over the label to see an explanation about the label's meaning, stating: "This provider is verified according to FAIRTAX and pays income tax for all bookings. The price shown includes all taxes."

[15] Thereby, we align the number of ratings towards the actual distribution of Airbnb listings (Ke, 2017b; Dann, Teubner, and Weinhardt, 2019; Cox, 2019).

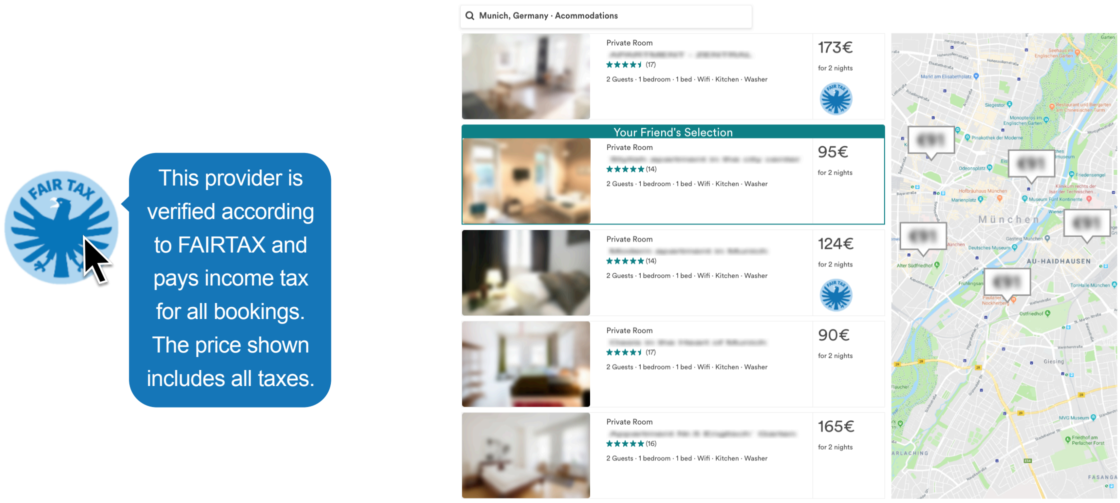

Figure 3.16: Tax Compliance Label Stimulus with Mouse Hover (left) and Exemplary Screenshot of overall Stimulus (right).

Prices For the prices, we select five different price levels, derived from the 25-, 50-, and 75-percentiles of comparable listings on Airbnb (Teubner, Hawlitschek, and Dann, 2017). Rounded to the nearest integer, we thereby generate the following set of prices: (1) 25-percentile -5%: €90, (2) 25-percentile: €95, (3) 50-percentile: €124, (4) 75-percentile: €165, and (5) 75-percentile +5%: €173. These five prices are allocated to the five listings at random whereby we ensured that the pre-selected listing is either associated with 25- (low) or 75-percentile (high) price.

Table 3.20: Stimulus Elements

Element	Manipulation
Amenities	Constant for each listing—private room in apartment: 2 guests, 1 bedroom, 1 bed, WiFi, kitchen, washer.
Images	Randomly drawn (without replacement) for each listing and participant from set of five blurred images of real Airbnb listings.
Titles	Randomly drawn (without replacement) for each listing and participant from set of five blurred titles from real Airbnb listings.
Star Rating	Randomly drawn for each listing and participant 4.5 or 5 stars. The selection always has 5 stars.
#Ratings	Randomly drawn for each listing and participant between 14 and 17—aligned towards the 75-percentile of comparable Airbnb listings.
Tax Compliance Label	Treatment-based: Either the pre-selection and one other random listing has the label or the pre-selection has no label and two other random listings have it.
Price	Randomly drawn (without replacement) from a set of five prices—aligned towards the 25-, 50-, and 75-percentile of comparable listings on Airbnb. The pre-selected listing either has the 25- or the 75-percentile price.

Measures

All measurement instruments of this study are based on validated scales. We adapt the operationalization of intention to book (ITB) from Gefen and Straub (2003), moral norm (MN) from Botetzagias, Dima, and Malesios (2015), and trust in provider (TIP) from Pavlou and Gefen (2004). All construct items were measured using 7-point Likert scales. Beyond these constructs, we survey demographic traits as control variables. These include age, gender, individual risk propensity (Dohmen et al., 2011), general trusting disposition (DTT) (Gefen and Straub, 2004), P2P familiarity (Gefen and Straub, 2004), and experience with taxes. All measurement instruments are listed in Table E.14.

Procedure and Sample

Participants have been recruited from the student subject pool at a large European university using the software *hroot* (Bock, Baetge, and Nicklisch, 2014). We incentivize participants with monetary rewards (equalizing €10.26 per hour and person). The median time spent in the experiment amounts to 9.09 min and 362 participants have started the experiment. 286 participants pass all attention checks and finish the experiment and survey completely. The resulting sample size is well above the threshold of samples needed for most applications (Hair, Babin, and Krey, 2017). Following power calculation, this sample size is appropriate for effect sizes d=.50 and α=.05 (Faul et al., 2007).

Within this sample, 34% are female, average age is 23.57 years (SD=3.91) with a minimum of 18 and a maximum of 59 years. Risk affinity (scale from 0 to 10) is 4.96 on average (SD=1.85). Overall, 55.2% of participants state to have experience declaring (their own or someone else's) taxes. We summarize the sample characteristics in Table 3.21.

Table 3.21: Sample Demographics

	All		Treatment (n=145)		Control (n=141)	
Trait	Mean (SD)	Range	Mean (SD)	Range	Mean (SD)	Range
Female	.343		.171		.352	
Tax Experience	.552		.552		.553	
Age	23.6 (3.91)	18-59	23.8 (4.33)	18-59	23.3 (3.45)	18-37
Risk Affinity	4.96 (1.85)	0-10	5.09 (1.83)	0-8	4.82 (1.86)	0-10

3.4.5 Results

First, we analyze the overall treatment effects of the tax compliance label on intention to book (see Figure 3.17). A 2 (label: yes, no) $\times$ 2 (price: high, low) ANOVA reveals significant effects for both the tax compliance label (F(1,283)=7.88, p=.005), and price (F(1,283)=94.82, p<.001), and no significant second-order interaction effects. Subsequent post-hoc analysis (TukeyHSD) confirms the significant distances both for the tax compliance label

(D_{LAB-NO_LAB}=.391, p=.005) and price ($D_{LOW-HIGH}$=-1.36, p<.001). We list the main treatment effects for the groups in Table 3.22.

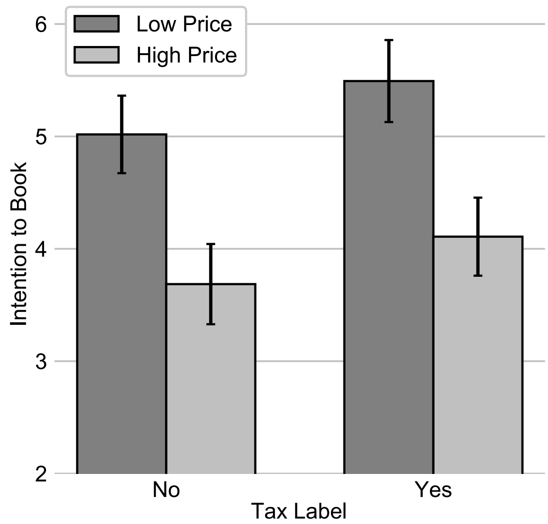

Figure 3.17: Main Treatment Effects.
Note: Continues variables (Moral Norms, Trust in Provider) split at median. Error bars indicate 95% confidence intervals.

Table 3.22: Main Effects on Intention to Book

	Available		Not Available	
Artifact	Mean (SD)	95% CI	Mean (SD)	95% CI
Tax Compliance Label	4.77 (1.29)	.215	4.38 (1.42)	.233
Low Price	5.24 (1.14)	.190	3.90 (1.24)	.206

Measurement Model

To initially explore the underlying factor structure of our measurement instrument, we conduct an Explonatory Factor Analysis (EFA) (Reio and Shuck, 2015). The EFA uses the Maximum Likelihood procedure and Promax Rotation resulting in an acceptable four factor model with all factor loadings greater than .50. Table 3.23 lists the adequacy measures. Table 3.24 provides the corresponding pattern matrix, item-level descriptives are provided in Table 3.25. We summarize construct descriptives, correlations, and reliability measures in Table 3.26.

We ensure internal consistency by confirming that all constructs fulfill the threshold of .70 for Cronbach's α and composite reliability (Bagozzi and Yi, 1988). Next, we confirm convergent validity by validating that all Average Variance Extracted (AVE) values exceed the .50 threshold (Hair, Ringle, and Sarstedt, 2011). Regarding discriminant validity, the Fornell-Larcker criterion (Fornell and Larcker, 1981) is met, and we observe no influential cross-loading values in the pattern matrix (Table 3.24).

Table 3.23: Adequacy Measures

Adequacy Measure	Value
Kaiser-Meyer-Olkin	.813
Bartlett's Test of Sphericity	.000
Communalities	.572
Non-Redundant Residuals	8 (6%)
Total Variance Explained	67.3%

Table 3.24: Pattern Matrix

	Factor			
Item	DTT	MN	TIH	ITB
ITB1				.725
ITB2				.702
ITB3				.823
MN1		.963		
MN2		.695		
MN3		.691		
TIH1			.649	
TIH2			.611	
TIH3			.686	
TIH4			.694	
DTT1	.854			
DTT2	.518			
DTT3	.762			
DTT4	.821			
DTT5	.913			
DTT6	.768			

Table 3.25: Item Descriptives

Item	Mean	St. Dev	Skewness	Kurtosis
ITB1	4.09	1.75	−.200	−1.13
ITB2	5.09	1.51	−.862	.006
ITB3	4.52	1.65	−.426	−.917
MN1	4.34	1.78	−.396	−.913
MN2	5.26	1.56	−1.09	.618
MN3	3.94	1.84	−.063	−1.19
TIH1	4.74	1.15	−.422	−.097
TIH2	4.22	1.25	−.218	−.542
TIH3	4.38	1.12	.003	.810
TIH4	4.58	.998	−.246	.741

Table 3.26: Construct Descriptives, Reliability Measures, and Correlations

					Correlation Matrix			
	Mean (SD)	Comp Rel.	CR α	AVE	ITB	MN	TIH	DTT
ITB	4.57 (1.37)	.875	.788	.700	.837	.154	.304	.117
MN	4.51 (1.49)	.881	.821	.714		.845	.013	.142
TIH	4.48 (.859)	.840	.716	.636			.798	.366
DTT	4.48 (1.12)	.921	.896	.665				.816

Note: Square roots of AVE on the diagonal of the correlation matrix.

Confirmatory Factor Analysis

We proceed with the Confirmatory Factor Analysis (CFA) using AMOS 26 (IBM, 2019). Following the guidelines of Hair, Babin, and Krey (2017), we determine the factor structure within our dataset and to test our hypotheses. To assess assumptions of multivariate normality, we confirm values within the range of ± 2.2 for both skewness and kurtosis (Table 3.25; Skarpness, 1983). For all models, we compare model fit by means of five fit indices, following the guidelines and thresholds of Hu and Bentler (1999).[16] For our initial model, we observe χ^2=161.7, p<.001, χ^2/df=2.61, CFI=.941, SRMR=.052, RMSEA=.075, PClose=.002, indicating an insufficient model fit (particularly regarding the PClose value). Based on the standardized residual covariances, we decided to drop DTT3 for the subsequent analysis. The resulting model achieves good model fit regarding all fit measures: χ^2=145.4, p<.001, χ^2/df=1.73, CFI=.965, SRMR=.054, RMSEA=.051, PClose=.452.

Measurement Model Invariance To ensure that the observed factor structure and loadings are equal across groups, we run invariance tests using a gender-based participant split. The model shows good fit, when assessed with both groups unconstrained (χ^2= 332.2, df=196, χ^2/df=1.695, CFI=.934, SRMR=.061, RMSEA=.049, PClose =.527), confirming configural invariance. Next, comparing the measurement model to the unconstrained model, we observe no significant difference (χ^2= 19.6, df=16, p=.237), meeting the requirements for metric invariance (Schmitt and Kuljanin, 2008).

Common Method Bias To account for potential Common Method Bias (CMB), we conduct a test of an unmeasured method factor (Podsakoff et al., 2003; Gaskin and Lim, 2017). We find that the unconstrained model is invariant from the constraint to zero model (unconstrained model: χ^2=53.0, df=98; zero constrained model: χ^2=90.0, df=98; delta: χ^2=37.0, df=588, p>.999). We conclude to observe no CMB and remove the unmeasured method factor for creating our factor scores.

Manipulation Check To ensure that our externally manipulated treatment conditions are perceived as such by the participants, we included two manipulation checks in our survey (Table E.15). Figure 3.18 depicts the manipulation's effect on the respective

[16] The recommended thresholds are: χ^2/df>.95, CFI>95, SRMR<.09, RMSEA<.05, and PClose>.05.

items. The visual impression of a discernible difference in the means across the groups is supported by separate two-sided Mann–Whitney U tests showing significant difference for both the tax compliance label (U=3418.5, p<.001) and the price conditions (U=1287.0, p<.001). Consequently, we conclude that the manipulation was successful.

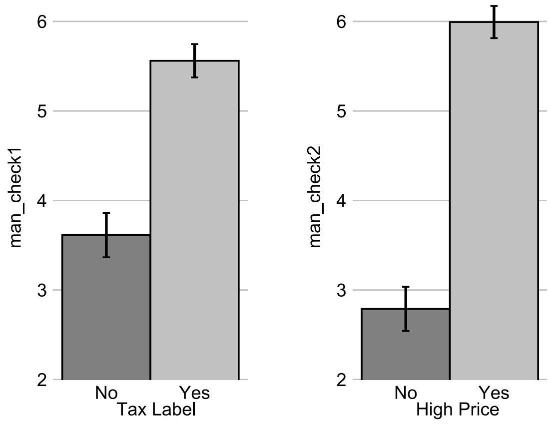

Figure 3.18: Manipulation Check for Tax Compliance Label (left) and Price (right).
Note: Error bars indicate the 95% level confidence intervals.

Structural Model and Hypotheses Testing

We build our structural model using the composites imputed from the previously validated measurement model's factor scores. We validate the multivariate assumptions of the generated composites by evaluating Cook's distance values. We observe no values larger than .008 indicating no multivariate influential outliers (Aguinis, Gottfredson, and Joo, 2013). Regarding multicollinearity, all observed variance inflation factors are below the 3.0, and tolerance values above the .10 threshold, indicating no multicollinearity issues (O'Brien, 2007). The final model (Figure 3.19) shows good model fit (χ^2=6.62, df=5.00, χ^2/df=1.32, CFI=.994, SRMR=.020, RMSEA=.034, PClose=.595), allowing us to interpret the estimated path coefficients.

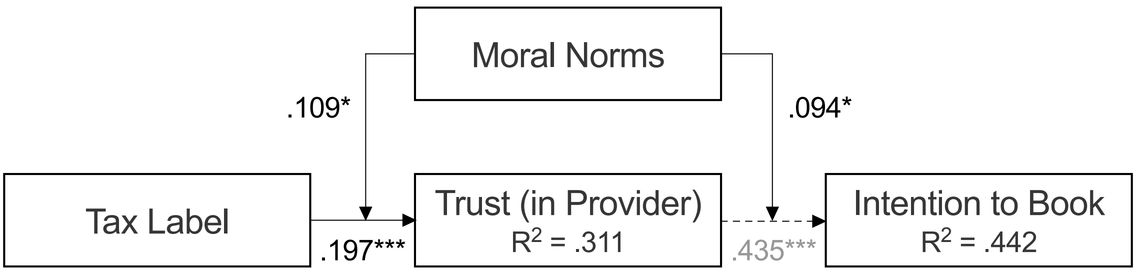

Figure 3.19: Standardized Estimate Results of Structural Model Testing.

The model explains 44.2% of the variance in consumers' intention to book and confirms all hypothesized relations. We observe a positive and significant effect of the tax compliance label on trust in provider (H_1,β=.197, p<.001). Further, this effect is stronger for consumers for which tax compliance is in accordance with their moral norms

(H_2,β=.109, p=.026). While the expected positive relationship between trust in provider and intention to book is also reflected in the model (β=.435, p<.001), it further shows that, consistent with our hypothesis, this effect is stronger for consumers for whom tax compliance is in accordance with their moral norms (H_3,β=.094, p=.035). Figure 3.20 depicts the moderation effects.

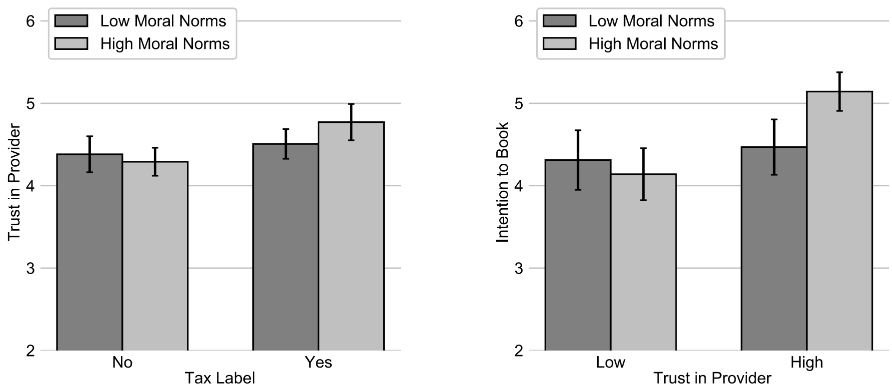

Figure 3.20: Left: Moral Norms × Tax Compliance Label on Trust in Provider (H_2). Right: Moral Norms with Trust × Trust in Provider on Intention to Book (H_3).
Note: Continues variables (Moral Norms, Trust in Provider) split at median. Error bars indicate 95% confidence intervals.

Control Variable Analysis

Next, we analyze the influence of the secondary variables on our structural model and hypotheses (Table E.15). Control variable analysis shows three significant effects. First, participants overall trusting disposition positively affects trust in provider (β=.504, p<.001). Second, male participants show a lower level of trust in the provider (β=-.132, p=.007). Third, the listing's price negatively influences booking intentions (β=-.441, p<.001). None of the control variables alters our findings in terms of magnitude, sign, or significance.

Monetary Equivalent of the Tax Compliance Label

The two employed price levels (see Table 3.20) allow us to calculate a monetary equivalent that participants assign solely to listings holding the tax compliance label. A price increase of €10 corresponds, on average, with a decrease of .194 points on the intention to book 7-point Likert scale. Contrasting this to the difference in the stated booking intention influenced by the label itself delivers a proxy for the monetary equivalent of €23.12 (Δ=.450).

Qualitative Assessment

To better understand participants' perception of the tax compliance label, as part of the online experiment, we collected qualitative feedback in the form of short free texts. We ask each participant to "please describe in your own words how the aspect of assuring tax compliance (i.e., the FAIRTAX label) has affected your evaluation of the selected listing." We collected 286 responses, which we classify on three levels. First, we assess whether the tax compliance has a general influence on booking decisions or not. Second, we classify whether a stated influence is perceived to be large or small. Third, we classify each response according to a set of 11 topic-based categories (Table 3.27).

Table 3.27: Categorization Schema

#	Category	Label's Influence
	Tax compliance (i.e., the label)	
1	...increases trust/competence/transparency of the provider	Given and large
2	...serves as signal/differentiation	
3	...justifies small surcharge	
4	...is a social responsibility	
5	...is an additional criterion for equivalent providers	Given and small
6	Other factors are more important	
7	Credibility of the label is unclear	
8	Tax compliance (i.e., the label) plays no/little role	Not given
9	Cheapest price is decisive	
10	Solely the provider is responsible for tax matters	
11	Labels are not very helpful in general	

To create the set of categories, three researchers independently screened each response and generated a set of categories. Subsequently, categories were discussed, refined, and synthesized. Across responses, we observe a the distribution of categories as depicted in Figure 3.21.

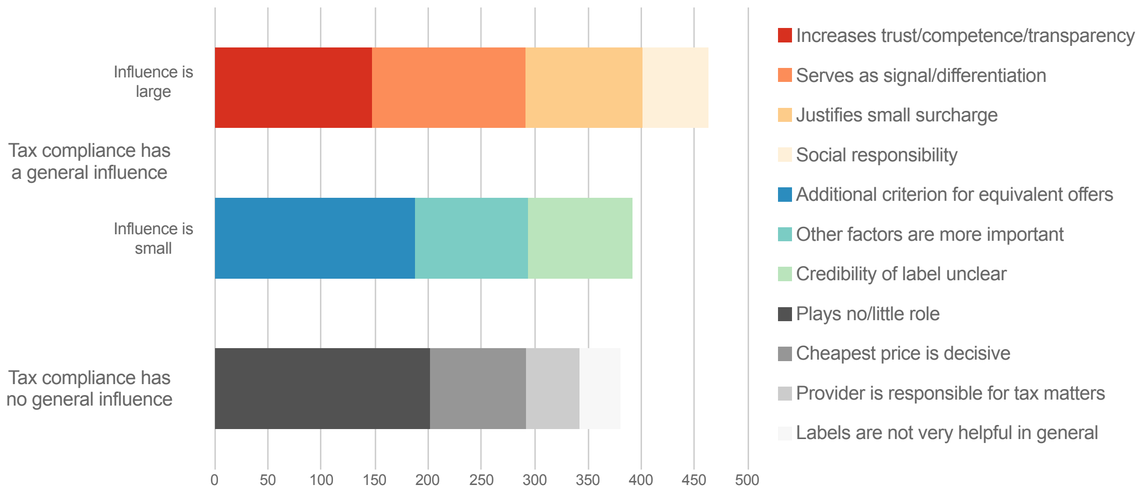

Figure 3.21: Categorization of Participant Responses. Categorization was non-exclusive (i.e., each response can be assigned to multiple categories).

Regarding inter-rater reliability, the final classification yields an average Fleiss' Kappa score of .660, indicating substantial agreement among raters (ranging from 394 indicating fair agreement to .850 indicating perfect agreement) (Landis and Koch, 1977).

The majority (69.2%) of the respondents state to perceive an influence of the tax compliance label (37.5% large; 31.7% small). Among the answers stating to perceive a large influence, participants predominantly highlight the labels trust-, competence-, and transparency-fostering effect (31.8%) and regard it as a signal with differentiating character (31.3%). Further, participants describe the label as a signal that justifies a small surcharge (23.5%) and marks social responsibility (13.4%). Statements referring to a small influence mainly consider the tax compliance label as a further criterion if the offers are otherwise equal (47.7%), but consider other things more important (27.3%) and express uncertainty regarding the label's credibility (25.0%). Participants that do not observe a general influence are strictly price-oriented decision-makers (23.4%), have a strict understanding of tax responsibility as a matter for the provider exclusively (13.4%), or question the usefulness of labels in general (10.0%).

3.4.6 Discussion

In this paper, we study the effects of tax compliance labels on consumers' booking intentions on P2P sharing economy platforms. While platforms such as Airbnb have established artifacts allowing consumers to assess providers' otherwise unobservable trustworthiness and service quality (e.g., text reviews, star rating scores, number of reviews), providers' tax compliance behavior is, as of today, not subject to signaling. Providers' tax compliance, however, is of utmost importance from an economic and societal perspective. This holds specifically given the substantial tax revenue associated with peer-based accommodation sharing and the competitive dynamics in the respective markets where maintaining "a level playing field" is the ultimate goal for public institutions (European Commission, 2016, p. 13).

Theoretical Implications

There is a diverse body of P2P platform literature that examines how different design artifacts influence consumers' perception of potential transaction partners. Nevertheless, our study is the first to examine the effectiveness of labels in the context of individual platform users' tax compliance by means of an online experiment. Thus far, existing literature mainly considered visual labels as signals of various quality dimensions directly related to the associated service or product of the transaction (e.g., Airbnb's Superhost label Teubner, Hawlitschek, and Dann 2017; Ke 2017b; Liang et al. 2017). Extending signaling theory to the context of tax compliance labels through our study emphasizes the theory's robustness. Thereby, tax compliance may constitute a relevant factor for achieving a separating equilibrium, where some consumers regard provider tax compliance as a necessary condition to consider an offer at all. The responses to our open-ended question highlights this relationship. In this, participants stated that:

"I would filter the listings without the tax compliance label" (Participant 203, 26, male).
"I would use a tax compliance label filter" (Participant 96, 19, male).

While providers' tax compliance is not directly linked to the quality of the service they provide per se (e.g., their service quality or their apartment), it does impact consumers' evaluation of the provider and leads to an increased willingness to pay. Thereby, we show that signaling tax compliance seems to induce a kind of cross-context signaling, which helps providers to establish the image of a trustworthy transaction partner (i.e.,

H_1)—ultimately reflected in booking intentions. Thereby, we emphasize the instrumental role of platforms in designing, creating, and maintaining an environment that allows for and stimulates trust-building (Kim, Yoon, and Zo, 2015). Our findings suggest that credibly demonstrating one's tax compliance represents a powerful lever in this regard.

"The tax compliance label shows that the provider pays their taxes and therefore should be more trustworthy" (Participant 146, 27, female).
"I would trust the provider more" (Participant 288, 20, female).

We contribute to theory by showing how individual normative concepts influence the effects of this label. We extend existing findings from research describing the influence of consumers' moral standards on the relationship of tax-compliant behavior and *corporate* reputation (Hardeck and Hertl, 2014; Hoopes, Robinson, and Slemrod, 2018) with an *individual* perspective. The effect of signaling tax compliance on trust in provider is stronger for participants who consider tax compliance as a moral obligation toward society (i.e., H_2). In addition, conformity of moral norms affects consumers' actual transaction intentions (i.e., their intention to book) and intensifies the positive relationship between trust in the provider and transaction intention (i.e., H_3).

"I would limit the variety of the available listings to my price budget and then choose from those that have such a tax compliance label to meet my moral standards and to ease my conscience" (Participant 261, 22, female).

Our assessment of the drivers behind participants' intentions provides a better understanding of how consumers evaluate providers and how, within this process, their moral norms guide their decisions. Previous literature, examining this context from a signaling perspective, primarily argues with the mere bridging of information asymmetry—whenever a signal is present, the associated quality is strictly given. However, our results indicate that the consideration of consumers' moral norms constitutes one necessary piece of the puzzle in understanding these relationships. In addition, moral norms as a whole seem to gain in importance since the 1980s (Wheeler, McGrath, and Haslam, 2019), and their relevance should not be neglected. This insight is especially important for studies in the context of P2P sharing platforms, since virtually all of these are directly associated with societal changes and, thereby, constitute no ordinary neutral markets. Particularly the case of P2P accommodation sharing is inherently burdened by emerging urgent conflicts (e.g., over-touristification, increasing rent prices, illegal hospitality operations), which today's media coverage increasingly focuses on.

Practical Implications

Our study further provides implications for platform users, operators, and policymakers. First, providers should be aware that consumers actually care about tax behavior, in turn rendering it a key driver of trustworthiness. Signaling tax compliance thereby helps to generate an overall honest and trustworthy appearance.

"I would consider the provider holding a tax compliance label to be more trustworthy, as he/she tries to behave correctly. I would also be under the impression that he/she is trying to act as honestly as possible" (Participant 318, 28, female).

Second, platform operators should consider implementing tax compliance labels. Such labels not only strengthen consumers' willingness to enter transactions with "tax-certified" providers, they also allow for charging price premiums for the associated offers. Our results indicate a feasible price markup of up to 18%. Some users even categorically refuse transactions with non-certified providers—an attitude, which may threaten the ongoing realization of transactions, and, thereby, the continued existence of a platform (Hodapp, Hawlitschek, and Kramer, 2019). Besides, it can be assumed that a proactive step towards tax compliance will certainly improve the platform's reputation (Hardeck and Hertl, 2014).

"I would also be willing to pay more for an apartment that has the tax compliance label" (Participant 362, 24 male).

Third, policymakers should actively engage platforms to install platform designs that include artifacts for signaling tax compliance. Considering the flexibility in the design of digital platforms, integrating such a tax compliance label seems to be an acceptable effort for platform operators and an effective means to take the first step towards a transparent taxation of transactions. Furthermore, implementing a tax compliance label would keep administrative efforts at a reasonable level for tax authorities, platform operators, and providers in ensuring tax compliance on P2P platforms (Fetzer Thomas, 2020). At the same time, it may increase compliance regarding self-reported income. In that, policymakers should consider both that consumers actually value tax-compliant behavior and that providers can also demand higher prices as compensation, which, in turn, may result in higher revenues for the platform. Basically, there are two options how such a tax compliance label may be granted to the provider.

First, one of the most conceivable ways is by having the platform deduct and transfer the tax component directly to the tax authority. Banks have a very similar practice for security portfolios (Ashauer-Moll Ellen, 2015), and several countries and municipalities have already arranged a co-operation agreement with Airbnb and implemented the taxation at source (i.e., via the sharing platform itself) for specific types of taxes such as occupancy taxes (Airbnb, 2020c). Beyond that, some countries implemented unilateral measures to ensure the taxation of the platform-related income. Belgium, for instance, has implemented a tax at source of 10% on certain types of sharing income (BRF Nachrichten, 2017). With this approach, the platform operator becomes liable for the collection and transfer of tax payments in every jurisdiction. Given that the platform operator has all necessary information available, granting the tax compliance label within this system of direct tax deduction becomes technically efficient. Policymakers worldwide are currently also debating on common rules for platform operators to share information on the transactions realized on their platform with national tax authorities (OECD, 2020). The exchange of information would enable tax authorities to identify and track cases of potential tax evasion. Moreover, a common reporting format would reduce complexity and keep the administrative burden for the platform operators at a reasonable level. Airbnb, for instance, has begun to show cooperativeness and goodwill in this regard (Kang, 2016; Airbnb, 2020a).

The second option for the certification procedure for tax compliant providers could follow three steps. (1): Providers give consent that the platform shares their transaction data with tax authorities, including name, address, tax ID, and details on realized transactions. (2): Tax authorities assess the information and compare it with income declared through the tax return. (3): The provider receives the tax compliance label if the tax authority confirms the correct and truthful declaration of income over the previous year(s). Obviously, providers may still decide not to declare their full income in future periods, but now at a higher risk of detection and prosecution. In other words, signaling tax compliance (e.g., through a tax compliance label) would be more costly for tax evaders. Besides, the verification of tax compliance by local tax authorities would substantiate the tax compliance label's credibility, which constitutes a concrete requirement for consumers.

In light of our findings, policymakers might explore novel forms of cooperation that include, for instance, the official certification of tax-compliant providers as outlined above. Such interaction with taxpayers would meet frequently raised calls by scholars for more service-oriented tax authorities and may improve intrinsic motivation for tax compliance (Pickhardt and Prinz, 2014; Batrancea et al., 2019). Overall, by ensuring tax compliance among providers, policymakers would create equal and fair competitive conditions among market participants and, thereby, might even strengthen the overall acceptance of the platform economy within the society.

Limitations and Future Work

We are aware of several limitations of our study. First, while all used stimulus materials are closely aligned to the look and feel of actual platforms, participants' statements within the online experiment may not properly reflect their behavior when using sharing platforms as consumers. Nevertheless, our experiment's scenario is inherently hypothetical. Other study designs (e.g., field experiments) might yield higher external validity. Second, our sample consists mostly of students within their 20's. However, while our sample represents the target and most active user group of P2P platforms (Mittendorf, Berente, and Holten, 2019; Godelnik, 2017; European Union, 2017), it also lessens our results' generalizability to the entire population or society as a whole. To ensure that our results are not driven by the most obvious covariates, we control for a broad set of variables, including age, gender, tax experience, disposition to trust, familiarity with P2P platforms, and general risk affinity. We explain 44.2% of the variance of consumers' transaction intention, which indicates potential for future research to investigate further drivers. Fourth, the "monetary equivalent" analysis provides only a first impression. For reliable numbers, longitudinal studies or conjoint-based studies are certainly more suitable for this particular aspect. Fifth, our study considers only the perspective of consumers. Aspects of what would motivate or deter providers from acquiring a tax compliance label remain unanswered at present. Finally, while we discuss options for how a provider may be granted the tax compliance label, this study does not describe the technical and legal details of such a certification procedure. In drawing the application and evaluation process, one certainly needs to consider a different stream of literature and even a different discipline within business economics (e.g., tax compliance and enforcement) and further details may be relevant for the label's perception by consumers. As some respondents state that they are uncertain about the credibility and origin of the label, further investigation of this aspect seems necessary. Moreover, future research should investigate potential spillover effects for platforms itself, which may improve their reputation just by offering a tax compliance label at all.

3.4.7 Conclusion

The issue of tax compliance is a socially highly relevant topic that is additionally burdened by a variety of aspects. These certainly include uncovered tax scandals such as the Panama Papers (Harding, 2016) or CumEx files (Reuters, 2019a) but also reports on the dimensions of tax avoidance by digital corporations (e.g., Apple; Schulze 2019 or Google; Reuters 2019b). As the emergence of the ride-sharing provider Uber has already shown, the dominant presence of P2P platforms poses challenges for regulatory institutions (Fitzsimmons, 2018). With our paper, we show that tax compliance on these platforms is perceived by consumers and constitutes reputational and monetary value—particularly when tax compliance is in line with consumers' moral norms. If existing (or new) platform operators do not seize the opportunity to address this topic proactively in order to enhance their reputation (Hardeck and Hertl, 2014), policymakers bear the social responsibility of incorporating our findings into adequate taxation concepts through regulatory adjustments.

Chapter 4

Finale

The previous chapters summarize four studies on the interplay of user representation, perceived social and economic values, and transaction intentions/behavior on P2P platforms. First, a structured literature review established a general understanding of P2P platforms' economics and which aspects existing literature has not sufficiently considered yet. These aspects were then examined in four studies: First, the overall role of user representation (UR) and how it relates to expected social and economic values and the ultimate intention to enter transactions. Next, the influence of UR on actual behavior across (multiple) transactions. Then, the influence of technological innovation on the need for trust among users. Last, the influence of signaling tax compliance within providers' UR on consumers' perception. This last chapter summarizes the contribution of the thesis, answers all raised research questions, and elaborates on existing limitations of the conducted studies as well as potential next steps of research.

4.1 Contributions and Answers to Research Questions

This thesis provides a comprehensive understanding of how social and economic values affect the initiation and conduction of transactions on P2P platforms. The studies presented cover (at least to some extent) all topics of existing literature that were identified in the preceding literature review (Chapter 2.1) (i.e., user motives and types, reputation systems, text reviews and self-descriptions, profile photos, prices and pricing value, economic and media impact, legal and regulatory aspects). This chapter summarizes the answers to each research question and summarizes the main contributions.

RQ1: *How do different UR artifacts facilitate co-usage transactions through social and economic value?*

As discussed in Chapter 3.1, a scenario-based online experiment is employed to answer this question. Participants took the role of a consumer evaluating the UR of a specific provider. The results show that self-descriptions, an artifact providing personal information, induces expectations about the social value of a transaction and star ratings, an artifact providing exogenous information, induces expectations about economic value.

The presence of a text review, an artifact providing personal *and* exogenous information, excerts an effect on both motives. Ultimately, both expectations about social and economic value drive transaction intentions in about equal shares.

Given this particular strength of text reviews, platform operators may consider allowing new transactions only after the previous transaction has been evaluated with a text review. However, as this is likely to result in more non-authentic reviews, platform operators should at least encourage and support platform users to always write a text review (e.g., by providing templates or text examples).

Furthermore, platform users should be aware of the strengths of each individual artifact within their UR. Even artifacts requiring comparatively low effort to obtain (e.g., the self-description) influence the evaluation as a potential transaction partner. However, they are currently not used by everyone (e.g., only about half of all Airbnb providers have written a self-description; Ke, 2017b).

Besides, platform operators should be aware of the importance of social *and* economic value for the creation of transactions. In line with the attempt of major platforms to expand their business model regarding social experiences (e.g., tours by local guides, local cooking courses; Airbnb, 2016a), platform operators may even consider to recommend or match transaction partners using social criteria. While this is of course directly tied to challenges in avoiding social discrimination and harassment, aspects such as having the same (or deliberately different) hobbies or interests could be included in the process of matching providers and consumers.

RQ2: *How does the interplay of cognitive and affective trust cues affect trusting behavior in sharing transactions over time?*

This next question, discussed in Chapter 3.2, focuses on actual behavior across (multiple) transactions. Within a laboratory experiment, participants formed (multiple) transaction dyads themselves and conducted a transaction with each selected transaction partner. Treatment-based, participants UR within the experiment included a (self-provided) profile photo and/or star ratings. The availability of star ratings or profile photos showed a distinctly different effect on trusting behavior. While the cognitive trust cue star ratings (associated with the central route of processing), showed a stable effect, the effect of the affective trust cue (associated with the peripheral route of processing) varied—depending on the specific transaction phase. However, the combination of both types of trust cues showed the most substantial effect on trusting behavior. These findings indicate that cognitive and affective trust cues are complementary over time. Furthermore, the results show that existing assumptions about the static influence of trust cues (Mcknight, Cummings, and Chervany, 1998; McKnight, Choudhury, and Kacmar, 2002) do provide an incomplete picture of their influence on trusting behavior.

The results stress the importance of the dual role of information processing (Petty and Cacioppo, 1986) for platform design. Trust cues processed via the central route need to be treated differently than trust cues processed via the peripheral route. While affective trust cues allow a "kick-starting" of trust in early phases of (novel) users or platforms to overcome the "cold-start problem" (Wessel, Thies, and Benlian, 2017), cognitive trust cues ensure that this increased level of trust does not collapse back to its initial level later on.

Overall, platform operators should encourage users to leverage both types of trust cues. While, on some platforms, users do not actively use these trust cues, there exist platforms, on which they are not available at all (e.g., Craigslist, Gumtree; Hesse et al., 2020).

RQ3: *How do blockchain-enabled platforms frame consumers' trust perception and their intention to enter a transaction?*

Chapter 3.3 addresses the influence of the technological innovation blockchain as the technical layer of a P2P platform on consumers' perception of the platform itself and providers on it. As the blockchain is supposed to act as a trust-building factor and may enable the creation of trust-free systems, the study investigates how the trust-related properties of the blockchain technology influence platform users' trust relationships. Within a scenario-based online survey, participants took the role of consumers evaluating a blockchain-based P2P platform.

The results provide evidence that, on blockchain-based platforms, trust in the transaction partner or the product itself shows no effect on the intention to enter a transaction. In this context, solely trust in the platform itself was an antecedent of transaction intentions. The study shows how established trust relationships shift from a peer and product focus towards trust in platforms and their underlying technology. Platform operators may leverage the blockchain technology to increase the level of trust that users place in the platform. This may also constitute a practical way to address the aforementioned cold-start problem as a new platform. In combination with established trust cues, a platform could thus foster transactions from the very beginning and ensure that a sufficient level of trust is maintained in later phases of platform evolution.

RQ4$_a$: *How does the presence of a tax compliance label affect consumers' trust towards and, in turn, their intentions to book at the tax-compliant provider?*
RQ4$_b$: *How do individual moral norms moderate the effect of tax compliance labels?*

Last, Chapter 3.4 discusses P2P platforms from a societal perspective. Focusing on providers' tax behavior on P2P platforms, the presented study examines how signaling tax compliance affects consumers' perception and choice of a transaction partner. To this end, the study introduces a label for tax compliance within providers' UR. In an online experiment, participants evaluated several offers of providers, of which some had this label for tax compliance, and some did not.

The results show that consumers are aware of providers' tax behavior and that tax compliance constitutes a trust-enhancing signal for which they are willing to pay a premium. Furthermore, consumers' moral norms positively moderate both the trust-building effect of tax compliance and the subsequent effect on transaction intention. In light of the current policy debate about taxing the platform economy, the study provides valuable practical insights for tax legislators. In particular, public institutions should actively engage in cooperation with platform operators to ensure tax compliance among users. In this regard, a label-based approach may represent one step towards their ultimate goal to level the playing field in the platform economy (European Commission, 2016).

4.2 Limitations

The applicability of presented results have to be considered in light of several individual limitations. First, the underlying participants of answering Research Questions 2, 3, and 4 stem from a pool of undergraduate students at the Karlsruhe Institute of Technology. Thereby, the sample is inherently subject to the characteristics of a student sample. Even though this specific group of users is the explicit target group of P2P platforms (Mittendorf, Berente, and Holten, 2019; Godelnik, 2017; European Union, 2017), and each study incorporates a comprehensive set of demographic control variables, it lessens the overall applicability of the individual results.

Next, all studies lack, to some degree, external validity. Perceptions about social and economic values, as well as the decision to enter a transaction on a P2P platform, may differ from the statements made within scenario-based surveys and online/laboratory experiments. Although all used stimulus designs are closely aligned to the look and feel of actual platforms, some of the outlined scenarios (i.e., blockchain-based platform, tax compliance label on a platform) are hypothetical. Field experiments may constitute a viable complement for the presented studies.

Subsequently, each study considers an individual set of UR artifacts. Although, across all studies, the influence of the most common UR artifacts is examined (i.e., profile photos, self descriptions, text reviews, star ratings, labels; Hesse et al., 2020), there exist various other artifacts that have not been included (e.g., membership duration, certificates, videos).

Last, apart from Chapter 3.2, all of the presented studies exclusively cover the perspective of consumers. Aspects of what would motivate providers to obtain a tax compliance label or offer their product/service on a blockchain-based platform remain unanswered.

4.3 Future Research

There exist various research opportunities to follow this thesis. This last chapter highlights three possible topics for future research. These include (1) the emergence of the technological innovation of virtual reality, (2) further research on the taxation of P2P platforms and its users, and (3) tackling existing discrimination.

Virtual Reality To establish trust, providers not only provide photos depicting themselves, they also provide photos of their offered assets (e.g., accommodation, car). However, the presented photos, may create a biased impression, since, for instance, a provider (consciously) only shows the pleasant parts of an accommodation, but not the unpleasant ones. Future research may address this problem of information asymmetry by exploring the potential of virtual reality in this context. Analogous to the blockchain, virtual reality is an emerging technology whose influence on the P2P platform economy is barely explored. While corporations are already embracing the potential of virtual reality in their online appearances (e.g., 360-degree representations of hotel rooms, cars, or commodities), it is still rarely used on P2P platforms. Given that existing research has already shown that virtual reality has a positive influence on buying intention (Suh and Lee,

2005) and travel desirability (Gibson and O'Rawe, 2018), P2P platforms should also leverage the merits of this technology.

In this manner, providers on P2P platforms may create 360-degree photos of their assets, which potential consumers could then view in a virtual reality representation using a head-mounted display. Thereby, they might get a more detailed and realistic impression of the offered assets. Since today's mobile phones' capabilities and available apps overcome prior technical barriers for creating 360-degree photos, it should be quite feasible for providers to integrate them into the presentation of their offers. Studying the perceptions of consumers of this representation, whether they can develop a better impression of the asset or overall situation they are expecting, whether this leads to a (perceived) reduction of information asymmetry, and whether this increases trust in the offer and the transaction partner, represents a natural next step for research.

Taxation of P2P platforms The study presented in Chapter 3.4 represents the first step in the analysis of tax-compliant behavior on P2P platforms. However, there still remain further subjects of investigation for this societally highly relevant topic.

First, this relates to technical investigations of how taxes can be paid directly via the platform to the responsible tax authorities. As emphasized in Chapter 3.4, in this context, aspects such as credibility and transparency should bear special consideration. Especially with regard to transparency, this context might be a possible field of application for the blockchain, which is frequently associated with this aspect (see Chapter 3.3). Future research may investigate the effectiveness of the blockchain for a transparent taxation of P2P platform transactions. Second, it remains unanswered as to what motivates *providers* to (not) behave tax-compliant. Whether this is primarily related to the prospect of higher (net) earnings, to a general unawareness of the issue, or a lack of knowledge about how to actually behave tax compliant is currently unclear.

Discrimination The existence of social interaction within transactions on P2P platforms where, at the same time, users share a variety of demographic traits results in undesirable side effects such as racial discrimination (Kakar et al., 2018; Edelman, Luca, and Svirsky, 2017). Although platforms deliberately speak up against discrimination through statements (Airbnb, 2019; Benner, 2016), their ultimate influence on the eventual discriminatory behavior of specific user groups is limited.

In times of the Black Lives Matter movement (Blum, 2020), the grievances on P2P platforms, that African-American providers are forced to demand lower prices (Edelman and Luca, 2014), or are rejected as transaction partners more often (Edelman, Luca, and Svirsky, 2017), should be tackled more intensively. While, during the emergence of P2P platforms, the prevailing direction was to disclose more and more information within the URs, future research should examine whether the reduction of demographic characteristics within URs may prevent discrimination. This poses a challenging task for platform designers, as they have to balance trust among users and avoid racial discrimination at the same time. One existing mechanism for reducing discrimination is the instant booking feature, which allows consumers to enter transactions without providers' prior review. The question of why only a minority of providers provide the option of instant booking (Table A.1), and how these rates could be increased should be examined by future research.

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Appendix

A Supplementary Material for Chapter 2.1

Table A.1: City summary

Region, City		#T	#Listings	Density	Date	#Hosts	R/L	Price (US$)	Score	Inst.B.	Ent.Apt	Prf.Lst
NA	Asheville	1	864	9.7	04/2016	643	32.1	99	95.32	.19	.62	.43
	Austin	3	9,663	10.2	03/2017	7,492	13.9	160	95.85	.23	.69	.36
	Boston	3	4,870	7.2	10/2017	2,705	24.8	140	93.37	.35	.62	.60
	Chicago	2	5,207	1.9	05/2017	3,532	25.4	99	95.04	.29	.59	.48
	Denver	2	3,918	5.7	11/2017	3,030	32.8	100	96.63	.44	.68	.42
	Los Angeles	11	31,253	7.9	05/2017	20,810	20.8	100	94.21	.27	.58	.51
	Montreal	2	10,619	6.1	05/2016	8,368	9.2	55.2	92.39	.14	.60	.35
	Nashville	4	5,332	7.8	09/2017	3,425	31.9	149	96.53	.49	.76	.51
	New Orleans	27	5,215	13.3	03/2018	3,050	36.3	132	95.71	.56	.83	.59
	New York City	35	48,852	5.7	03/2018	40,530	18.5	100	93.56	.31	.49	.32
	Oakland	2	1,718	4.1	05/2016	1,427	15.6	98	93.96	.11	.56	.34
	Portland	29	4,738	7.4	02/2018	3,793	49.5	90	96.81	.41	.66	.37
	Quebec City	9	2,297	4.3	09/2017	1,662	22.7	64	93.41	.41	.63	.45
	San Diego	2	6,608	4.7	07/2016	4,300	14.1	135	94.38	.18	.66	.52
	San Francisco	29	4,804	5.6	03/2018	3,346	49.9	150	95.79	.36	.58	.51
	Santa Cruz	1	814	3.0	10/2015	616	27.2	150	94.86	.10	.65	.40
	Seattle	2	3,818	5.4	01/2016	2,751	22.2	100	94.54	.15	.67	.43
	Toronto	7	12,714	4.5	06/2017	9,152	16.0	76.8	94.00	.21	.62	.44
	Vancouver	4	6,651	10.3	10/2017	5,050	22.5	92	94.13	.26	.68	.41
	Victoria	1	1,691	19.7	08/2016	1,256	18.5	80	94.53	.21	.67	.44
	Washington D.C.	3	7,788	11.4	05/2017	5,820	19.5	125	94.72	.30	.68	.40
AS	Hong Kong	1	6,474	0.9	08/2016	3,334	12.7	70.59	88.44	.25	.50	.61
AU	Melbourne	8	14,305	3.7	04/2017	10,506	16.3	81.9	94.02	.29	.57	.41
	Northern Rivers	1	2,350	7.9	04/2016	1,703	10.6	114.27	93.85	.13	.65	.47
	Sydney	12	32,830	8.1	01/2018	25,221	10.3	104.52	93.28	.34	.61	.36
	Tasmania	18	4,459	8.7	02/2018	3,038	31.2	116.22	95.54	.51	.76	.48
EU	Amsterdam	28	18,547	22.6	12/2017	15,907	18.2	141.6	94.41	.20	.79	.24
	Antwerp	2	1,227	2.5	05/2017	968	21.6	76.7	92.33	.26	.70	.36
	Athens	2	5,127	7.7	05/2017	3,535	24.2	47.2	94.23	.51	.83	.54
	Barcelona	21	18,531	11.5	02/2018	10,909	27.6	69.62	90.76	.45	.47	.60
	Berlin	19	20,576	5.9	05/2017	17,810	12.9	53.1	93.39	.17	.50	.25
	Brussels	2	6,192	5.4	05/2017	4,623	18.0	64.9	91.45	.25	.65	.39
	Copenhagen	2	20,545	26.9	06/2017	19,079	10.7	105.92	94.39	.15	.81	.16
	Dublin	3	6,729	12.8	02/2017	4,756	21.0	93.22	91.99	.26	.47	.47
	Edinburgh	10	9,638	19.5	09/2017	7,175	26.9	94.47	94.69	.35	.57	.42
	Geneva	19	3,060	15.7	01/2018	2,361	15.5	96.305	93.42	.28	.66	.41
	London	6	53,904	6.1	03/2017	37,642	12.5	93.8	91.71	.23	.50	.45
	Madrid	6	16,313	5.2	01/2018	9,838	27.7	69.62	92.43	.48	.63	.57
	Malaga	1	4,853	8.5	11/2017	2,386	20.2	69.62	91.00	.57	.76	.70
	Mallorca	2	14,858	17.1	03/2017	6,323	7.4	118	91.88	.36	.87	.71
	Manchester	1	865	1.6	04/2016	560	17.2	62.98	91.18	.17	.41	.52
	Paris	28	59,945	26.7	03/2018	51,683	16.3	88.5	92.49	.27	.87	.25
	Rome	1	25,275	8.8	05/2017	14,100	22.6	82.6	91.99	.45	.60	.65
	Trentino	1	1,847	1.7	10/2015	1,275	3.1	82.6	91.39	.13	.77	.55
	Venice	2	6,027	22.8	05/2017	2,860	35.8	129.8	91.16	.50	.75	.73
	Vienna	22	9,201	5.2	09/2017	6,522	20.8	64.9	93.84	.36	.67	.44

Notes: #T = number of available snapshots (months); Density = Listings per 1,000 capita; #R/L = number of reviews per listing; Inst.B. = Instant Booking; Ent.Apt = Entire Apartment; Prf.Lst = Professional Listing (i.e. host offers more than one); NA = North America; AS = Asia; AU = Australia; EU = Europe
Source: Data from InsideAirbnb.com

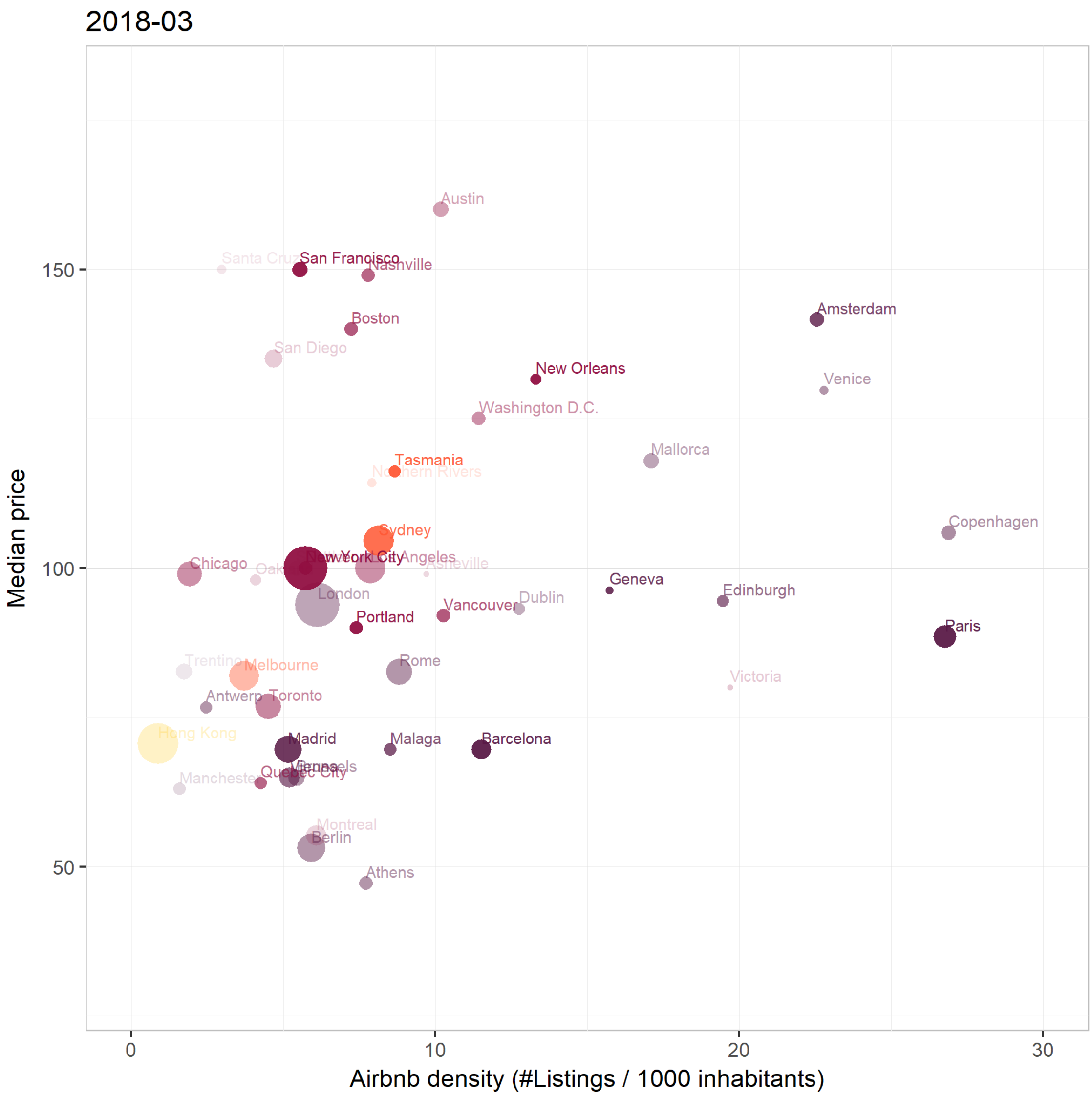

Figure A.1: Comparison of cities along the dimensions Airbnb density (#listings per 1,000 population) and median price ($US)

Notes: Bubble opacity indicates data recency. Data retrieved from InsideAirbnb.com. An animated version of this figure is provided at `https://im.iism.kit.edu/img/airbnb_cities.gif`.

B Supplementary Material for Chapter 3.1

B.1 Summary Table of Related Work

Table B.2: Related literature on value motives and user representation artifacts in the sharing economy.

			Tested Value Motives		Tested UR Artifacts		
Publication	**Sample**	**Context**	**Social**	**Economic**	**SR**	**SD**	**TR**
Chiu et al. (2014)	782	e-com	.310	.450			
Bilgihan and Bujisic (2015)	334	acc	.415	.344			
Möhlmann (2015)	187	acc	n.s.	.230			
Bucher, Fieseler, and Lutz (2016)	498	misc	.350	.210			
Tussyadiah (2016a)	644	acc	.168	.269			
Barnes and Mattsson (2017)	115	misc	.205	.493			
Mittendorf and Ostermann (2017)	203	acc	n.s.	.220			
Hawlitschek, Teubner, and Gimpel (2018)	745	misc	.076	.231			
Lee and Kim (2018)	511	acc	.260	.220			
Lutz et al. (2018)	374	misc	n.s.	.200			
Oyedele and Simpson (2018)	345	misc	n.s.	n.s.			
So, Oh, and Min (2018)	519	acc	n.s.	.110			
Sung, Kim, and Lee (2018)	422*	acc	n.s.	n.s.			
Tussyadiah and Park (2018)	2,045*	acc	.190	.420			
Clauss, Harengel, and Hock (2019)	146	misc	.478	.132			
Henry et al. (2019)	500	misc	n.s.	.227			
Jiang, Balaji, and Jha (2019)	332	acc	.190	.100			
Kim, Karatepe, and Lee (2019)	393	misc	.360	n.s.			
Tsou et al. (2019)	460	misc	.680	.140			
Wang, Asaad, and Filieri (2019)	606	acc	.102	.116			
Wang et al. (2019)	378	misc	.360	.570			
Ye et al. (2019)	571	acc	.258	.472			
Zhang, Gu, and Jahromi (2019)	985	misc	.650	.100			
Ert, Fleischer, and Magen (2016)	270	acc			×		
Abrahao et al. (2017)	8,906	acc			×		
Abramova, Krasnova, and Tan (2017)	450	acc			×		
Fagerstrøm et al. (2017)	139	acc			×		
Ma et al. (2017)	355	acc				×	
Fagerstrøm et al. (2018)	30	acc			×		
Qiu and Abrahao (2018)	5,277	acc			×		
Tussyadiah and Park (2018)	301	acc				×	
Zloteanu et al. (2018)	430*	acc			×		×
Abrate and Viglia (2019)	981	acc			×		
Cheng et al. (2019)	30	acc					×
Heejeong (2019)	854	acc			×	×	×
Zhu, Lin, and Cheng (2019)	4,602	acc					×
This Study	486*	acc	.420	.424	×	×	×

Note: Numbers in the Tested Motives columns represent significant path coefficients; SR = star rating; SD = self-description; TR = text review; acc: accommodation sharing; e-com: e-commerce; misc: miscellaneous; *: multiple sub-samples

B.2 Measurement Instruments

Table B.3: Main Constructs, Items, and Sources.

Construct	Source	Code	Original Items	Adapted	Item Loading
Intention to Book (ITB)	Gefen and Straub (2003)	ITB1	I am very likely to buy ticket from Travelocity.com.	I would be very likely to book at this host.	.911
		ITB2	I would use my credit card to purchase from Travelocity.com.	I would stay at the apartment of this host.	.895
		ITB3	I would not hesitate to provide information about my habits to Travelocity.	I would not hesitate to request a booking with this host.	.877
Expected Economic Value (EEV)	Kim, Chan, and Gupta (2007)	EEV1	Compared to the fee I need to pay, the use of M-Internet offers value for money.	Compared to the costs of booking with this host, it would still financially benefit me to do so.	.940
		EEV2	Compared to the effort I need to put in, the use of M-Internet is beneficial to me.	Compared to the effort associated with booking with this host, it would still financially benefit me to do so.	.929
		EEV3	Compared to the time I need to spend, the use of M-Internet is worthwhile to me.	Compared to the financial risks I am taking, it would still benefit me to book with this host.	.905
		EEV4	Overall, the use of M-Internet delivers me good value.	Overall, it would financially benefit me to book a stay at this host's apartment.	.940
Expected Social Value (ESV)	Jiang et al. (2013)	ESV1	In the particular experience, I believed that the interaction would fulfill my social needs (for example, companionship, approval, acceptance, respect, status) in some way.	The interaction with this host would foster pleasant socializing (such as enjoyable conversations and company).	.885
		ESV2	In the particular experience, I believed that the interaction would help me cultivate a good relationship with the other party.	I would get on well with this host.	.863
		ESV3	In the particular experience, I believed that I could derive satisfaction from interacting with the other party.	It would be nice to get to know this host in person.	.825

Table B.4: Demographic and Control Constructs, Items, and Sources.

Construct	Source	Code	Item
Disposition to Trust	Gefen (2000)	DTT1	I generally trust other people.
		DTT2	I tend to count upon other people.
		DTT3	I generally have faith in humanity.
		DTT4	I generally trust other people unless they give me reason not to.
Risk Propensity	Dohmen et al. (2011)	RP	How do you see yourself: Are you prepared to take risks, or do you rather try to avoid them? Please tick a box on the scale, where the value 0 means: 'not at all willing to take risks' and the value 10 means: 'very willing to take risks.'
Experience (as host)	–	EXP	Describe your use of platform Airbnb as a host (never/ sometimes/ regularly)
Experience (as guest)	–	EXC	Describe your use of platform Airbnb as a guest (never/ sometimes/ regularly)
Gender	–	–	Specify your gender.
Age	–	–	How old are you?
Control	–	CTR	Please check the second box from the left.

B.3 Mediation Analysis

To elaborate in greater detail how much of the effect of the treatment variables on intention to book can be attributed to the paths via expected social value and expected economic value, we conduct a mediation analysis. The paths from self-description ($\beta =$ .055, n.s.), text review ($\beta =$ .034, n.s.), and star rating ($\beta =$ .061, n.s.) on intention to book, from self-description on expected economic value ($\beta =$ .045, n.s.), and from star rating on expected social value ($\beta =$ .022, n.s.) are insignificant (Figure C1). Furthermore, in this extended model, none of the hypothesized effects is altered regarding magnitude, sign, or significance. Consequently, the effects of all treatment variables on intention to book are fully carried through expected social and economic value.

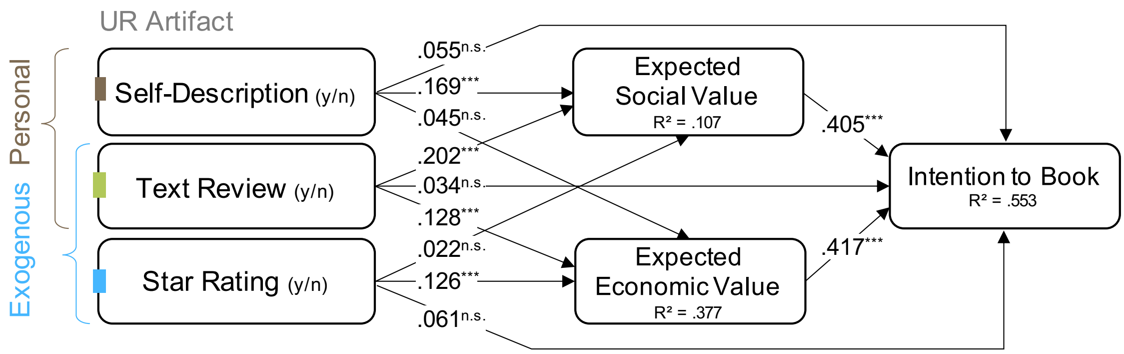

Figure B.2: Results of the Structural Model Testing for the Saturated Model

C Supplementary Material for Chapter 3.2

C.1 Star Ratings and Trusting Behavior

To shed further light on how the availability of star ratings contributes to engendering trust, we consider which star ratings were exchanged, how specific scores are associated with trusting behavior, and also how—in turn—behavior is reflected in star ratings.

To do so, we focus on the corresponding subset in which star ratings were available (n=72). First, it strikes the eye that the distribution of exchanged star rating scores greatly resembles distributions observed on actual peer-to-peer sharing platforms (Figure C.3; mean=4.09 stars, SD=1.17) with 5 stars being the most frequently used score (50% of all cases). In this regard, the experiment's rating distribution is consistent with what is typically observed on contemporary peer-to-peer platforms and review sites (Schoenmüller, Netzer, and Stahl, 2018; Teubner and Glaser, 2018).

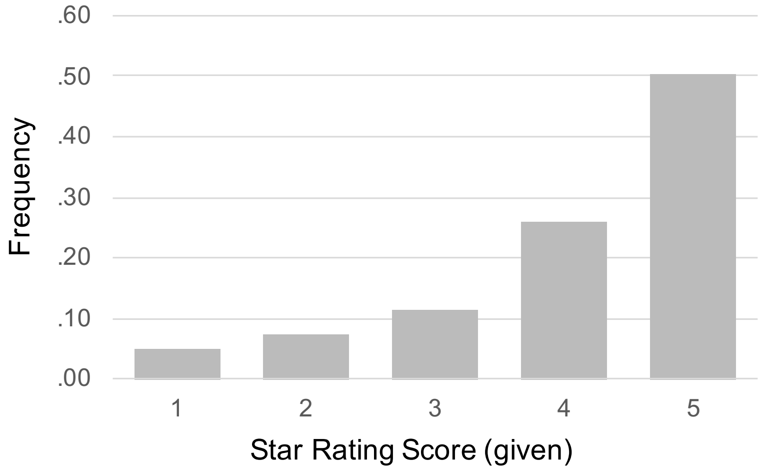

Figure C.3: Rating distribution (based on 396 star ratings from 198 completed transactions)

Second, as shown in Figure C.4, providers' trusting behavior (as per the transferred amount) is strongly correlated with the star rating they receive from the consumer (Pearson's r =.686, p <.001). Moreover, consumers' trustworthiness (as per the returned amount) is strongly correlated with the star rating they receive from the provider (r =.731, p <.001). Thus, within the scope of our experiment, star rating scores did, in fact, reflect (past) behavior and hence carried informational value (*star ratings as the result of behavior*).

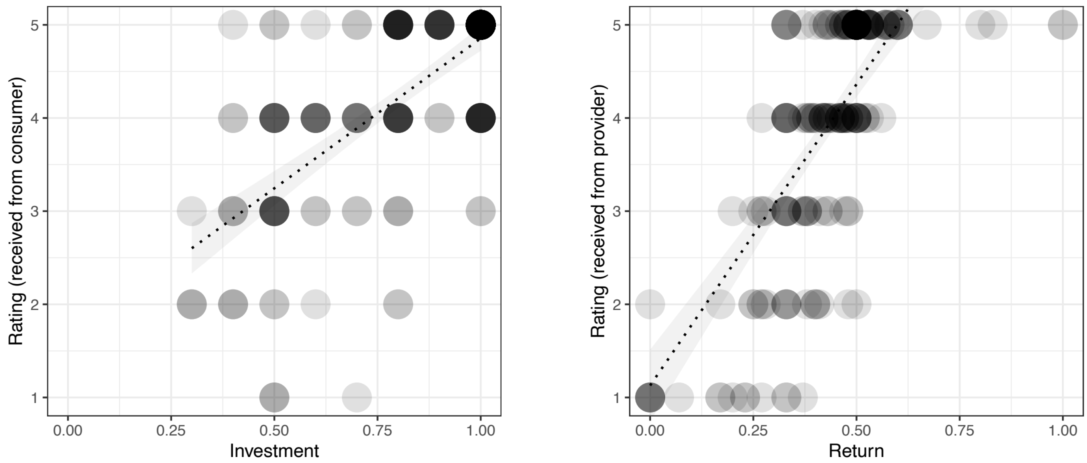

Figure C.4: Correlation of provider's trusting behavior (i.e., transferred amount), consumer's trustworthiness (i.e., returned amount), and the associated star ratings received from the respective other party

Third, we consider how the information carried in the average star rating scores translated into behavior, that is, *behavior as a result of star ratings*. To do so, we first consider whether consumers' *chances of being accepted* depend on their aggregated rating score. Moreover, once a transaction was initialized, we consider the *provider's trusting behavior* based on the consumer's current average star rating. Note that overall, 61% of all 645 sent requests were accepted. Thus, a considerable fraction of requests were actually declined, which is consistent with results from the platform literature (Edelman, Luca, and Svirsky, 2017; Fradkin, 2015; Karlsson, Kemperman, and Dolnicar, 2017). Table C.5 summarizes linear and logistic regression estimates for (1) the probability that a provider accepts a consumer's request and (2) the provider's trusting behavior. We find that higher star rating scores increase consumers' *chances of being accepted* ($\beta =$1.06, $p <$.001) and *higher levels of trusting behavior* once a transaction was realized ($\beta =$.130, $p <$.001).

Table C.5: Regression models for request acceptance and investment

	DV=Provider Accepts Request (yes=1, no=0)		**DV=Provider's Trusting Behavior [0, 1]**	
Consumer's average rating score$^{(1\text{–}5)}$	**1.06**	***	**.130**	***
	(.192)		(.017)	
Period$^{(0\text{–}5)}$	.177		**.039**	***
	(.092)		(.009)	
Treatment: Profile Photos$^{(\text{yes}=1)}$	.029		**.112**	***
	(.253)		(.025)	
Time to Accept/Decline$^{(\text{sec})}$	**.043**	**		
	(.015)			
Intercept	-5.32	***	.091	
	(.977)		(.087)	
Observations	298		162	
R^2	.172		.365	

Note: Ordinary least squares (provider's trusting behavior) and logistic (provider accepts request) regression models. DV=dependent variable; standard errors in parentheses; *** p<.001; ** p<.01; * p<.05. Moreover, note that the number of observations in these regression models is smaller than the overall number of requests (left-hand model) and transactions (right-hand model) as there occur cases in which no star rating score was available yet (e.g., in the first period).

Taken as a whole, the distributions of star rating scores observed in the experiment are comparable to those on contemporary peer-to-peer sharing platforms and also that the specific properties of the displayed star rating scores (qualitatively and quantitatively) carry meaningful information which both reflect past and impact future behavior.

C.2 Face Visibility, Attractiveness, and Visual Trustworthiness

As an additional control analysis, we take a closer look at the profile photos and how specific properties were associated with participant behavior. To do so, we focus on the corresponding treatment conditions for which profile photos were available (n=72). Note that in these treatment groups, *all* participants provided a profile photo. We consider face visibility (fully visible: 60; partly visible: 5; not visible: 7), attractiveness, and visual trustworthiness. Face visibility was assessed by manual inspection. Attractiveness and visual trustworthiness were assessed in an additional survey, complementing the main study's data. In this survey, an unrelated set of 16 respondents evaluated the main study's profile photos in terms of attractiveness and visual trustworthiness (each on a single-item 7-point Likert scale). On average, attractiveness scored at 4.24 (SD=.502) and visual trustworthiness at 4.26 (SD=.623). Inter-rater reliability was r_{wg}=.768 for the visual trustworthiness, and r_{wg}=.677 for attractiveness, suggesting adequate inter-rater agreement (James, Demaree, and Wolf, 1984).

We now consider whether, and if so, how this information translated into behavior, that is, *behavior as a result of specific photo properties*. Table C.6 summarizes the logistic and regular regression estimates for (1) the probability that a provider accepts a consumer's request and (2) the provider's trusting behavior (as per the transferred amount to the consumer). The results show that face visibility, visual trustworthiness, and attractiveness do neither significantly affect acceptance nor trusting behavior. This suggests that—compared to the paramount effect of profile photo availability as such—specific photo characteristics played a subordinate role within our experiment.

Table C.6: Regression models for request acceptance and trusting behavior

	DV=Provider Accepts Request		**DV=Provider's Trusting Behavior**	
Consumer Face Visibility$^{(yes=1)}$	-.221		.083	
	(.468)		(.063)	
Consumer Attractiveness$^{(1-5)}$	-.218		-0.34	
	(.280)		(.036)	
Consumer Visual Trustworthiness$^{(1-5)}$	.359		.002	
	(.315)		(.041)	
Consumer Gender$^{(female=1)}$	.064		.058	
	(.264)		(.033)	
Treatment: Star Ratings$^{(yes=1,\ no=0)}$	-.206		**.100**	**
	(.242)		(.032)	
Period$^{(0-5)}$	.031		.020	*
	(.068)		(.009)	
Time to Accept/Decline$^{(sec)}$	**.029**	*		
	(.013)			
Intercept	-.466		**.809**	***
	(.966)		(.132)	
Observations	330		201	
R^2	.033		.102	

Note: Ordinary least squares (provider's investment) and logistic (provider accepts request) regression models. DV=dependent variable; standard errors in parentheses; *** $p<$ .001; ** $p<$ .01; * $p<$ .05

C.3 Consumers' Returns

Analogously to provider's trusting behavior, we also analyze returns (i.e., how much consumers transfer back to providers; normalized to the interval [0, 1]). As depicted in Figure C.5, the joint availability of both trust cues yields return levels of about 43%, while for the absence of both yields 29%. If only one cue is available, returns are 38% for affective, and 43% for cognitive cues.

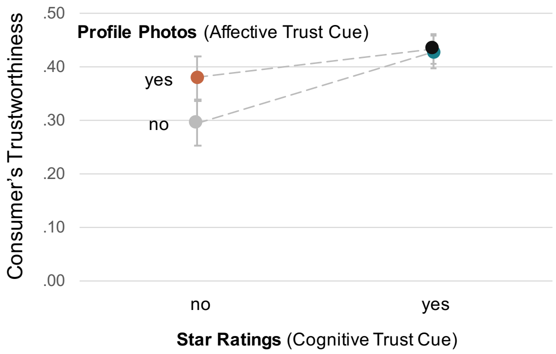

Figure C.5: Main treatment effects of trust cues on consumer's return

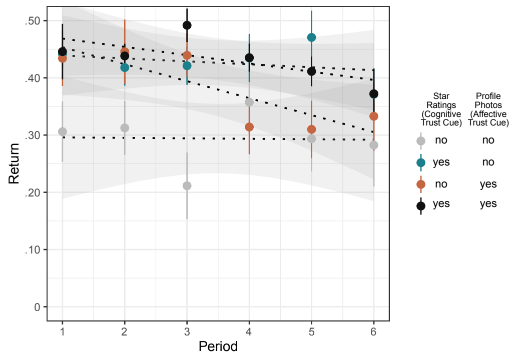

Figure C.6: Curse of consumer's return across periods

Figure C.6 shows the periodic-specific effects. We observe relatively stable or slightly decreasing returns overall, while there occurs a rather sharp decrease of return rates in the profile photos treatment condition. We assess the time-dependent effects with two random effects panel regression models. The models (Table C.7) take into account repeated measures (period 1 to 6) per subject with single returns as the unit of analysis (n=378).[1] Model I confirms a general treatment effect for star ratings (β =.078, p <.01) but not for profile photos (β =.018, p =.503). Providers' trusting behavior significantly influences return behavior (β =.202, p <.001).

Furthermore, the model shows a negative overall time effect (β =-.021, p <.001). Model II shows no significant time-treatment interaction but also a negative overall time effect (β =-.018, p <.05). Both star ratings and profile photos seem to have no effect in the first period (star ratings: β =.059, p =.079; profile photos: β =.054, p =.111). Again, providers' prior trusting behavior significantly influences return behavior (β =.199, p <.001). However, this finding is in line with previous work that describes return behavior as inherently dependent on—and mostly driven by—preceding trusting behavior. Thus, the analysis thereof is only of secondary interest (Bapna, Qiu, and Rice, 2017). None of the control variables (gender, age, experience) exert significant effects.

[1]Note that for 16 transactions, the provider's trusting behavior was 0 (i.e., no monetary units transferred to the consumer), and hence relative returns are nonsensical (division by zero). The set of transactions considered for returns hence only contains 378 (rather than 394) observations.

Table C.7: Regression models on returns (as an operationalization of consumers' ex-post trustworthiness)

	DV=Return			
	Model I		Model II	
Star Ratings$^{(\text{yes}=1,\ \text{no}=0)}$	**.078**	**	.059	
	(.026)		(.034)	
Profile Photos$^{(\text{yes}=1,\ \text{no}=0)}$	.018		.054	
	(.026)		(.034)	
Period$^{(0\text{–}5)}$	**-.021**	***	**-.018**	*
	(.005)		(.008)	
Trusting Behavior$^{(\text{Transferred Amount})}$	**.202**	***	**.199**	***
	(.037)		(.037)	
Star Ratings × Period			.008	
			(.009)	
Profile Photos × Period			-.015	
			(.009)	
Gender$^{(\text{female}=1)}$	-.018		-.019	
	(.027)		(.027)	
Age	.006		.006	
	(.005)		(.005)	
Experience$^{(\text{yes}=1)}$	.043		.044	
	(.029)		(.029)	
Intercept	.080		.073	
	(.110)		(.111)	
Observations	378		378	
R^2	.127		.135	

Note: Generalized linear models with subject random effect. DV=dependent variable; standard errors in parentheses; *** $p<.001$; ** $p<.01$; * $p<.05$

C.4 Trusting Behavior-Trustworthiness Effect Decomposition

Next, we take a closer look at the value that is captured by providers and how this effect can be decomposed into partial effects of their own trusting behavior (transferred amounts) and ex post trustworthiness exhibited by consumers (i.e., returned amounts). The payoff π_{it} a provider i receives in period t amounts to:

$$\pi_{it} = .5 + 1 + y_{it} \cdot (3z_{jt} - 1),$$

where y_{it} denotes the provider's trusting behavior, z_{it} is the relative consumer's trustworthiness j, and the absolute values of .5 and 1 denote the booking fee as well as the provider's endowment. Given this, we can decompose (i.e., factorize) π_{it} and examine the individual effects of y_{it} and z_{it}. To do so, we analyze the aggregated average trusting behavior and trustworthiness rates as well as the provider values across the four treatment conditions (Table C.8). Both for trusting behavior and trustworthiness rates, the treatment without any true cues yields the lowest rates, while the treatment with both true cue types yields the highest. The generated values reflect this pattern.

Table C.8: Average trusting behavior, trustworthiness, and provider's value (π) across treatment conditions

Treatment	**Provider's Trusting Behavior**	**Consumer's Trustworthiness**	**Provider's Value π**
Star Ratings=no, Profile Photos=no	.567	.294	.932
Star Ratings=no, Profile Photos=yes	.770	.380	1.11
Star Ratings=yes, Profile Photos=no	.757	.427	1.21
Star Ratings=yes, Profile Photos=yes	.882	.431	1.26

The baseline treatment exhibits both the lowest overall levels of trusting behavior and returns. Comparing the only-star-ratings with the only-profile-photos treatment shows that while trusting behavior was higher in the profile photos treatment, trustworthiness was higher in the star ratings treatment. Beyond these overall findings, Figure C.7 depicts the course of trusting behavior and trustworthiness across treatments and individual periods, providing more detailed insights into the development of these values. The iso-value lines indicate equal levels of π. Interestingly, for the only-star-ratings treatment, trusting behavior initially rises until the third period, while trustworthiness remains relatively constant. From the fourth period on, however, the return rates decline sharply, which subsequently is followed by lower levels of trusting behavior, causing the aforementioned inverted u-shape.

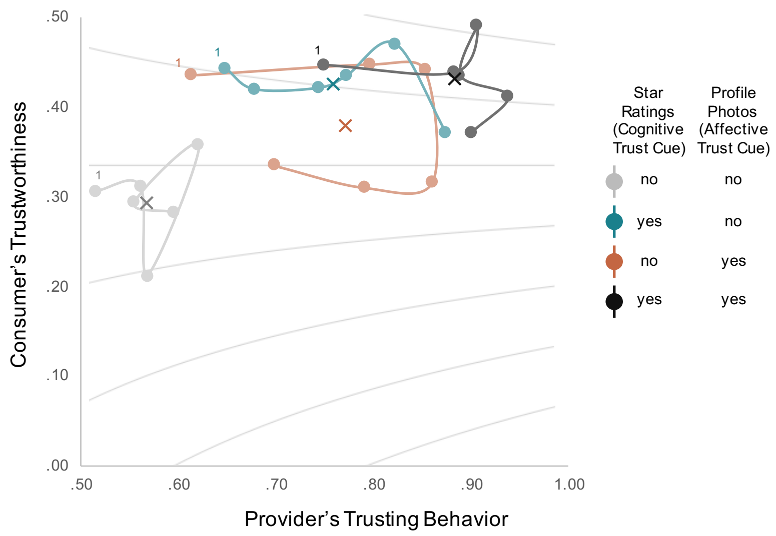

Figure C.7: Effect decomposition for each treatment condition throughout the six periods with iso-value lines. The curve of the photos-only treatment (orange) shows the inverted u-shape (tilted to the side)
Note: [1] denotes treatment's first period, $\times$ indicates overall average treatment value.

Considering the $\times$-marks in Figure C.7 illustrates along which partial effects the treatment conditions (and hence the trust cues) make a difference with regard to value capture by providers. As can be seen, "activating" either one of the cues increases both trusting behavior *and* trustworthiness since both colored marks lie further up and further right than the grey mark. While both of the cues yield similar trusting behavior, star ratings yield higher degrees of trustworthiness. This treatment difference can hence be attributed to the star ratings' effect on consumer rather than provider behavior. Now, considering how the additional value is captured when both cue types are present at the same time, we see that it is mainly the provider's trusting behavior that makes the difference.

C.5 Realization of Matches and Request Behavior

Realization of Matches Overall, we observe comparable numbers of realized matches—both across treatments as well as across periods—as expressed by the fraction of how many of all possible matches are actually realized. These rates exceed 90%, so that basically every participant is matched (and hence enters a transaction) in almost every period (see Table C.9).

Table C.9: Number of transactions in the respective treatment conditions

		Profile Photos	
		no	**yes**
Star Ratings	**no**	96	100
	yes	97	101

Request Behavior Next, we control for potential confounds regarding requesting behavior. Table C.10 shows how the rare cases that, in a given period, a participant did not (1) send at least one request (consumers) or (2) receive at least one request (providers) are distributed across the four treatment conditions.

Table C.10: Distribution of absent requests sent and received across treatments

Star Ratings	Profile Photos	Possible cases [1)]	Cases in which no requests were: . . . sent	. . . received
no	**no**	108	8	10
	yes	108	1	6
yes	**no**	108	0	10
	yes	108	0	5
Overall		432	9 (2.1%)	31 (7.2%)

Note: [1)] per treatment condition, there were 3 sessions · 6 participants · 6 periods

Table C.11 underpins the above observations by means of regression analyses. These models show that the presence of both trust cues (star ratings and profile photos) had no significant effect on the realization of transactions. However, we find that both star ratings ($\beta =$.042; $p <$.01) and profile photos ($\beta =$.032; $p <$.05) have positive effects on the share of participants (i.e., consumers) who sent at least one request (averaged by treatment *and* period). However, we do not find any significant influence of these treatment variables on the fraction of participants who *received* at least one request (i.e., providers). This suggests that the additionally sent requests are not spread out evenly across providers but concentrate on those who already receive requests from other consumers. Last, note that period did not affect the dependent variable in any of these models.

Table C.11: Regression models for share of requests sent, received, and realized transaction

	DV=Share of Realized Transactions		DV=Share of Requests...			
			...sent		...received	
Treatment: Star Ratings$^{(yes=1,\ no=0)}$	.009		**.042**	**	.005	
	(.021)		(.013)		(.023)	
Treatment: Profile Photos$^{(yes=1,\ no=0)}$	.037		**.032**	*	.042	
	(.021)		(.013)		(.023)	
Period$^{(0–5)}$	-.003		.002		-.006	
	(.006)		(.004)		(.007)	
Intercept	**.900**	***	**.935**	***	**.926**	***
	(.028)		(.017)		(.031)	
Observations	24		24		24	
R^2	.154		.474		.169	

Note: Ordinary least squares regression models. Data on "treatment and period" level (i.e., $n = 4 \cdot 6 = 24$); DV = dependent variable; standard errors in parentheses; *** $p<.001$; ** $p<.01$; * $p<.05$

C.6 Introductory material

This appendix includes the material provided to the participants in the experiments. Depending on the specific treatment condition, the material slightly differed in terms of whether (1) star ratings and (2) profile photos were available. This relates back to our 2 (star ratings: yes/no) × 2 (profile photos: yes/no) full factorial between-subjects treatment design (see Treatment Structure subsection in the body of the paper). The material shown in this appendix was specifically for the treatment condition where both star ratings and profile photos were available. All participants saw the welcome screen. Then, depending on the role that a particular participant was randomly assigned to, the participant either saw the material for a consumer or a provider.

Welcome

You are participating in an experiment from which you can earn money. During the whole experiment you will operate with monetary units (MU), which will be converted into Euros and paid out afterwards. A conversion factor of 4 MU = 1.00 € applies. The amount of your payoff depends on your behavior and the behavior of the other participants. The results at the end of each period you will play are decisive. The role you take in the experiment was randomly determined. You either take the role of a provider or a consumer. You will retain this role for the entire experiment.

The experiment randomly comprises between five and eight periods. Each period comprises two phases in which you can undertake different actions. At the end of each period, a summary and your payoff for this period is depicted. After the experiment, three of your periods are randomly selected and you get the payoffs from those periods paid out.

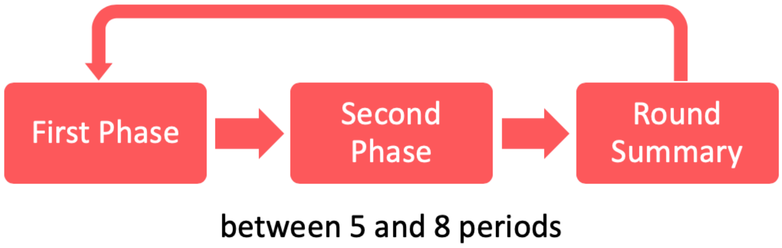

Figure C.8: Experiment overview

First Phase (Consumer)

Your role is **consumer**. Each period you receive an endowment of 10 MU. In the first phase, you can request providers to exchange MU with them in the second phase. You will see a list with information about the providers and the booking fee if a provider accepts your request. You will see a list with information about all providers including the applicable booking fee if a provider accepts your request.

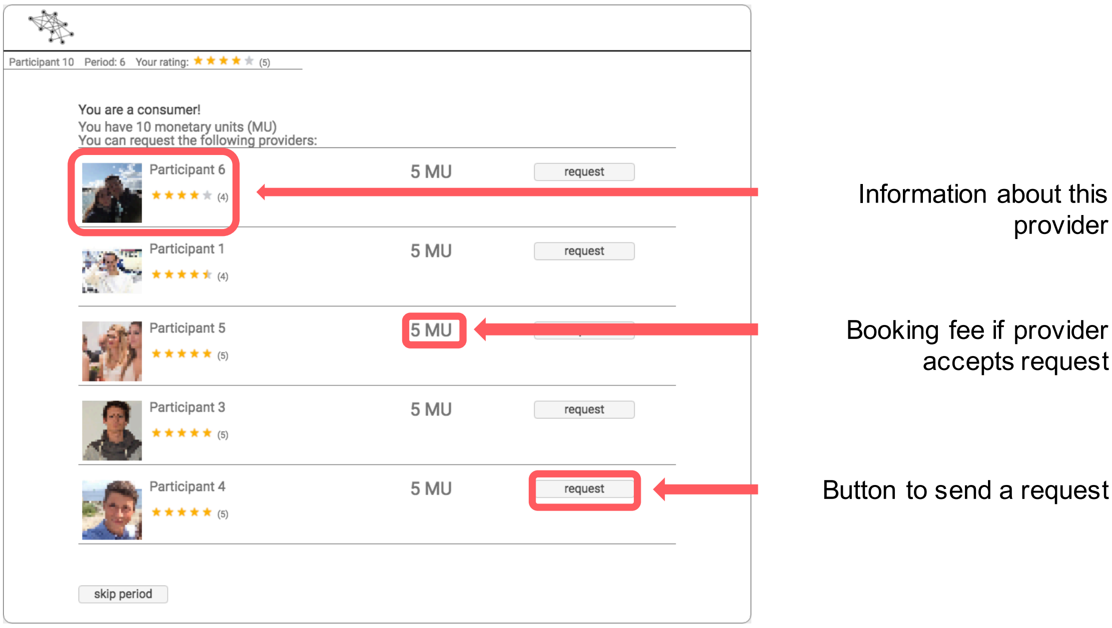

Figure C.9: List of providers

Providers that cannot be requested are marked with a “not available” label. You cannot request a provider who has declined your request in this period or who has already accepted another participant’s request. A provider who was your transaction partner in the previous period is not available and not displayed for two consecutive periods.

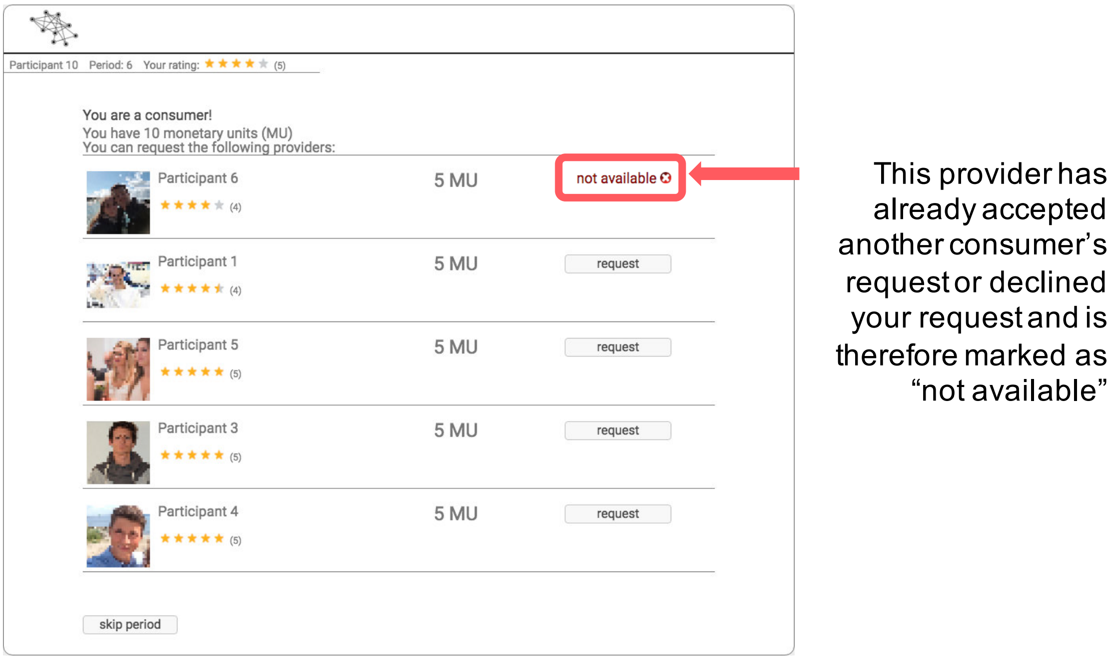

Figure C.10: Not available provider

Requests are valid for 30 seconds. The remaining time is shown by a countdown. During this time, you cannot send any further requests to other providers. Not processed requests within this time limit will be automatically withdrawn.

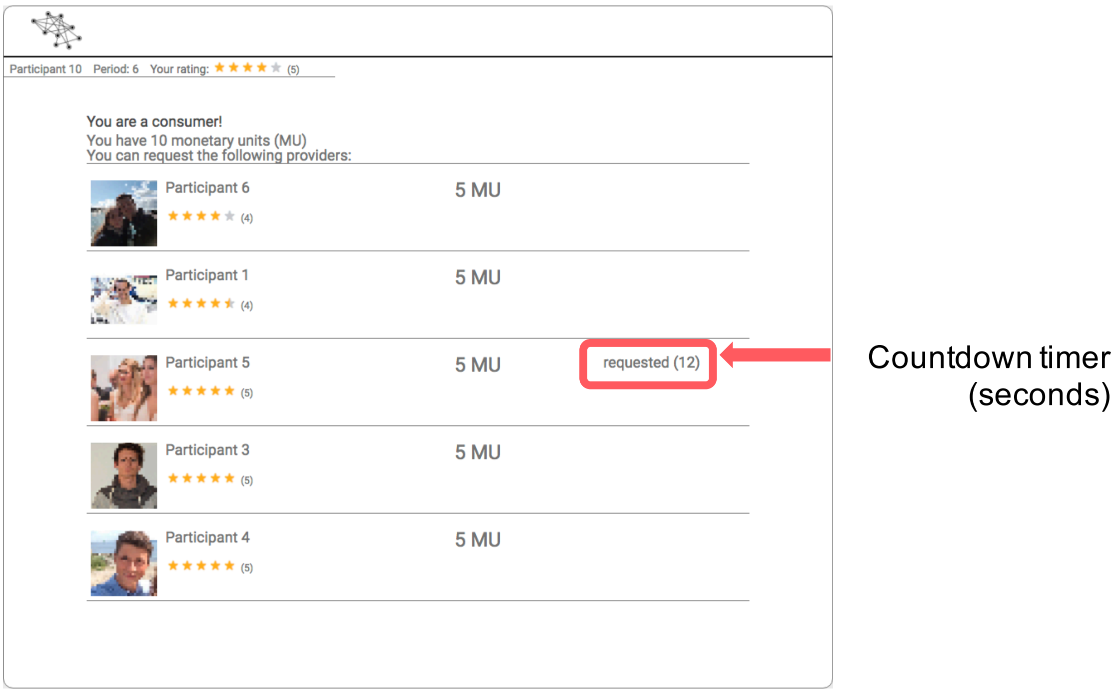

Figure C.11: Request countdown

As soon as a provider has accepted your request, a confirmation notification will appear on your screen. The 5 MU booking fee will be subtracted from your endowment and transferred to the provider. Clicking the "continue" button brings you to the second phase of the current period.

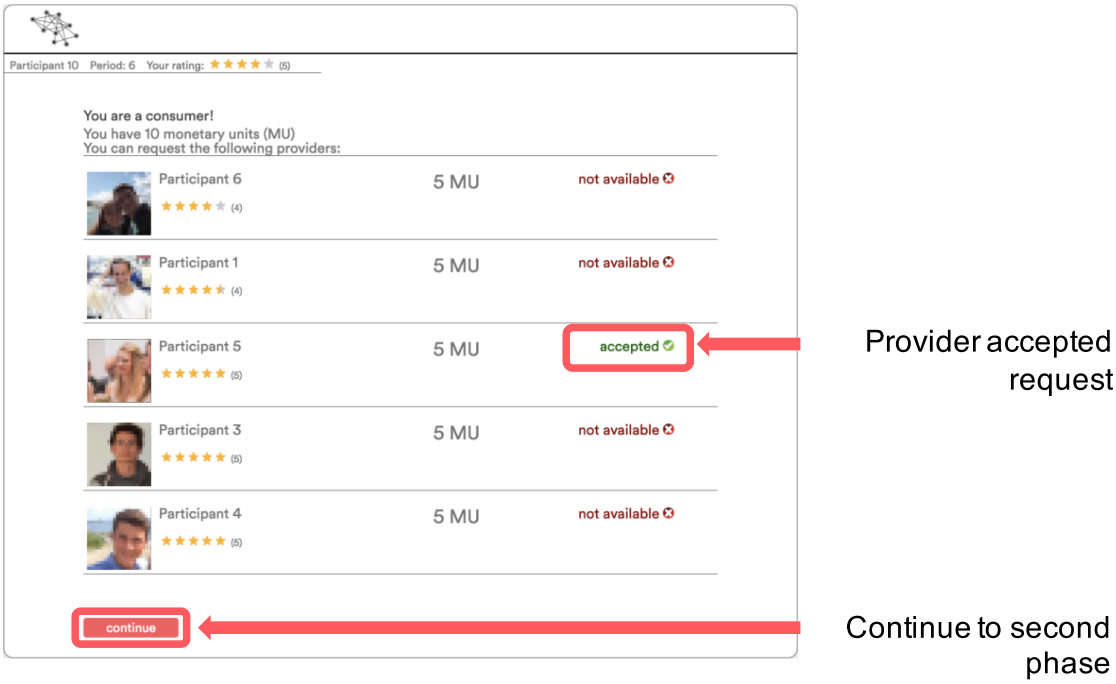

Figure C.12: Accepted request

If no provider is available for a request, you cannot participate in the second phase of this period. The "continue" button brings you directly to the period summary. Your payoff for this period will be your endowment (10 MU).

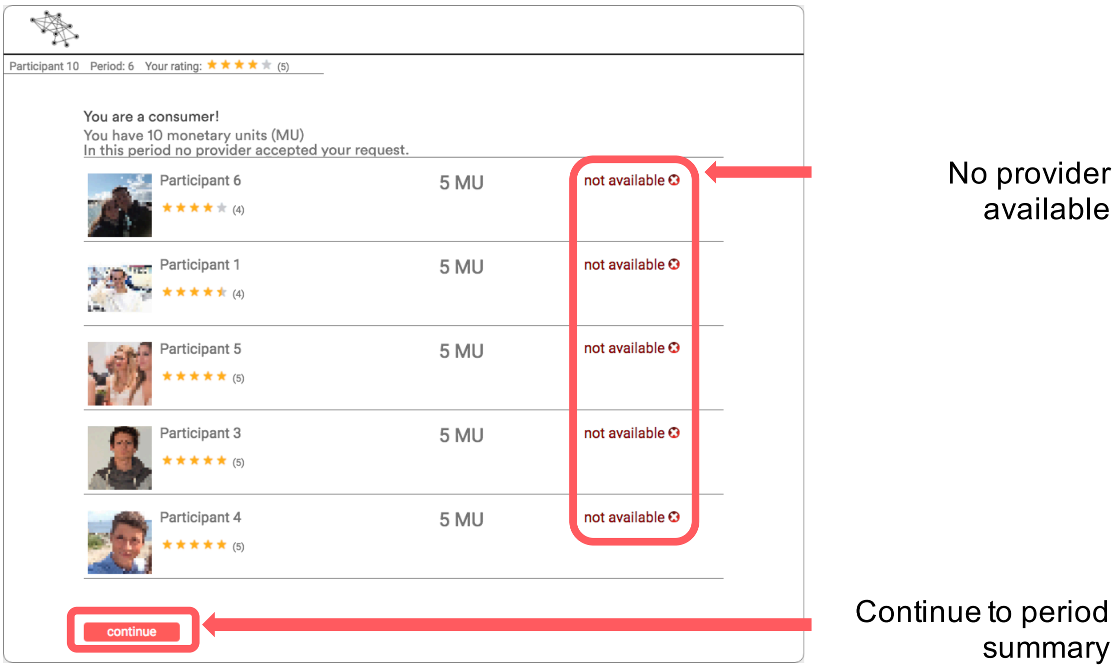

Figure C.13: No provider available

If you do not want to request any of the providers available, you can also skip the current period. You will then not participate in the second phase of this period. The "skip period" button brings you directly to the period summary. Your payoff of this period will be your endowment (10 MU).

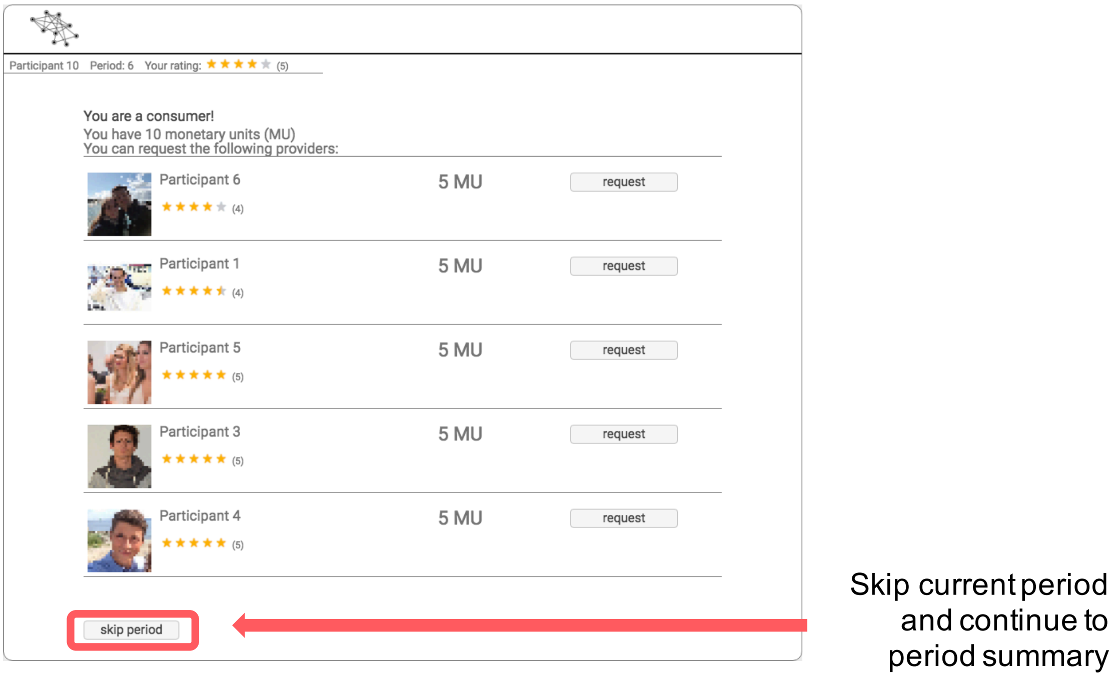

Figure C.14: Skip current period

Second Phase (Consumer)

The second phase begins with your transaction partner transferring an amount of MU to you. The amount the provider transfers to you is then tripled and added to your current period payoff. During this process, you will see a waiting screen.

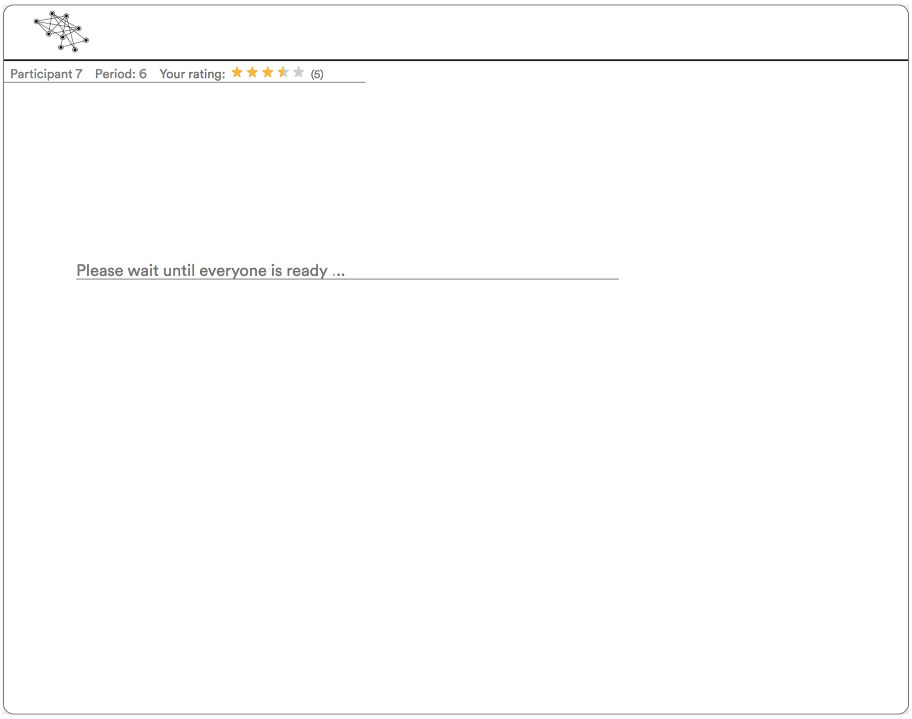

Figure C.15: Waiting screen

As soon as the provider has chosen the amount to be transferred to you, you will have to decide via a dropdown bar how much of the tripled amount you want to transfer back to the provider. This amount will be added to the provider's period payoff (without further tripling). Confirming your choice with the "continue" button brings you to the period summary.

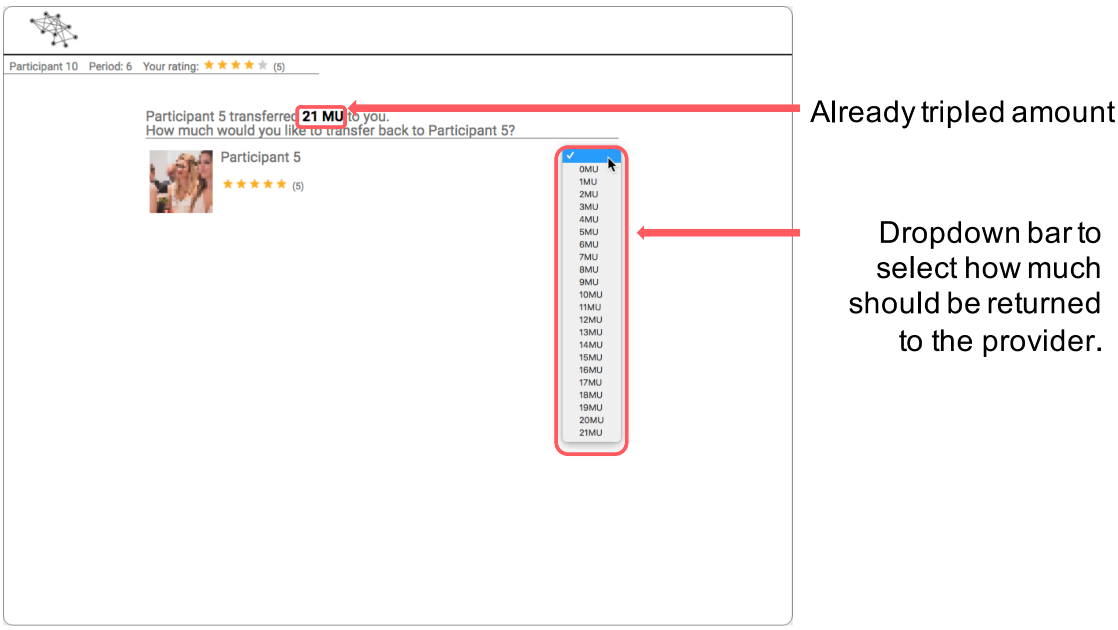

Figure C.16: Return to provider

Period Summary (Consumer)

The period summary will show you your payoff for this period. Using the five-star rating system, you must evaluate your partner for this transaction. You will also receive a rating for this period from your transaction partner. Confirming your rating with the continue button brings you to the first phase of the next period.

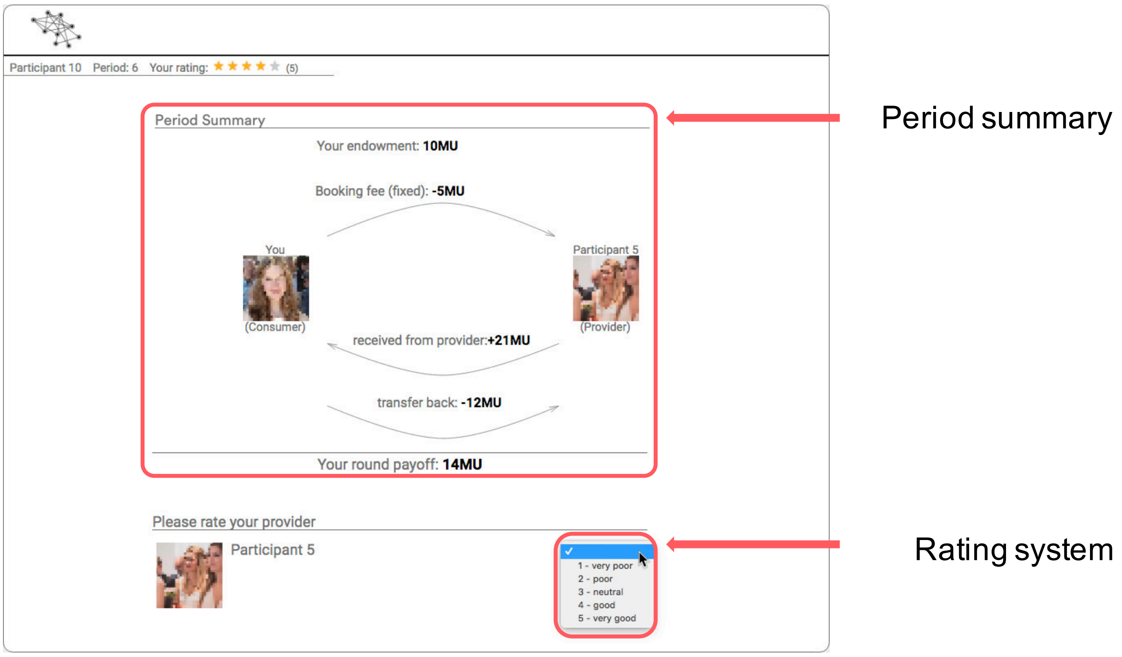

Figure C.17: Period summary (consumer)

Comprehension Questions (Consumer)

With the following questions you can check whether you have understood the rules of this experiment. The statements are either true or false. Please check the correct answer.

		True	False
1.	At the beginning of each period my endowment is 10 MU.	O	O
2.	I am assigned the same interaction partner in each period.	O	O
3.	Providers with whom I interacted in the previous period are blocked for one period.	O	O
4.	If I don't have an interaction partner in a period, my payoff for that period is 10 MU.	O	O
5.	My final payoff in € at the end of the experiment depends on the results of my periods.	O	O
6.	If a provider accepts my request, I will pay him a booking fee of 5 MU.	O	O

Figure C.18: Comprehension questions (consumer)

First Phase (Provider)

Your role is **provider**. Each period you receive an endowment of 10 MU. In the first phase you will receive requests from consumers from whom you can choose one to exchange MU with in the second phase. The list of current requests contains information about the consumers who sent you a request as well as buttons to accept or decline a request.

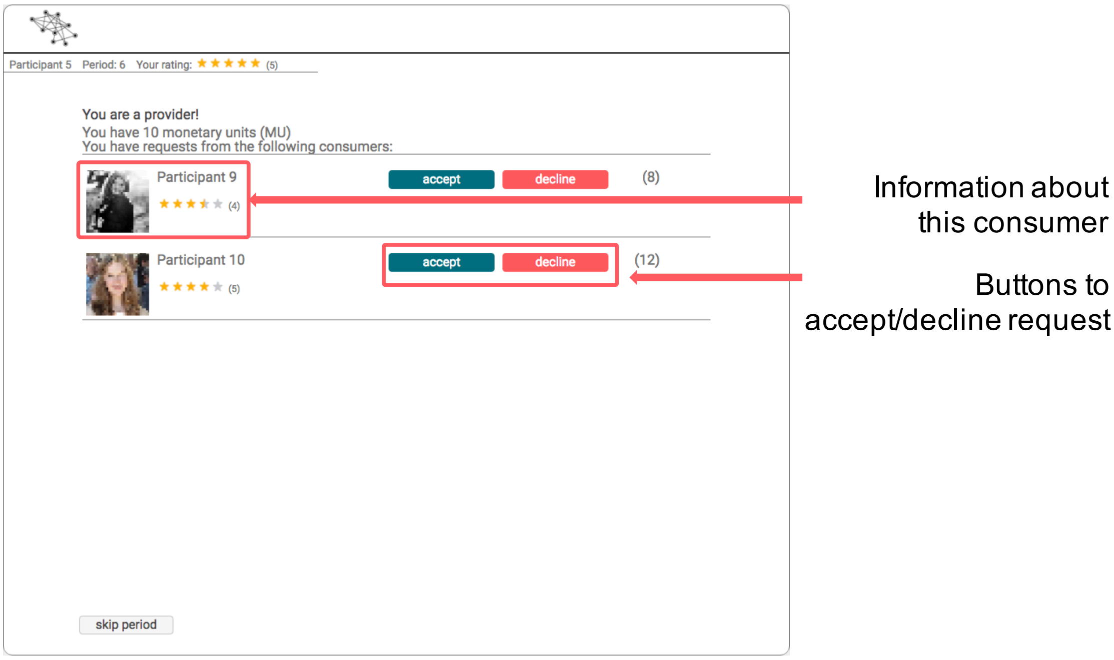

Figure C.19: Available consumer requests

Consumer requests are valid for 30 seconds. The remaining time is indicated by a timer next to the buttons to accept/decline a request. If you do not process a request within this time limit, it will be automatically withdrawn.

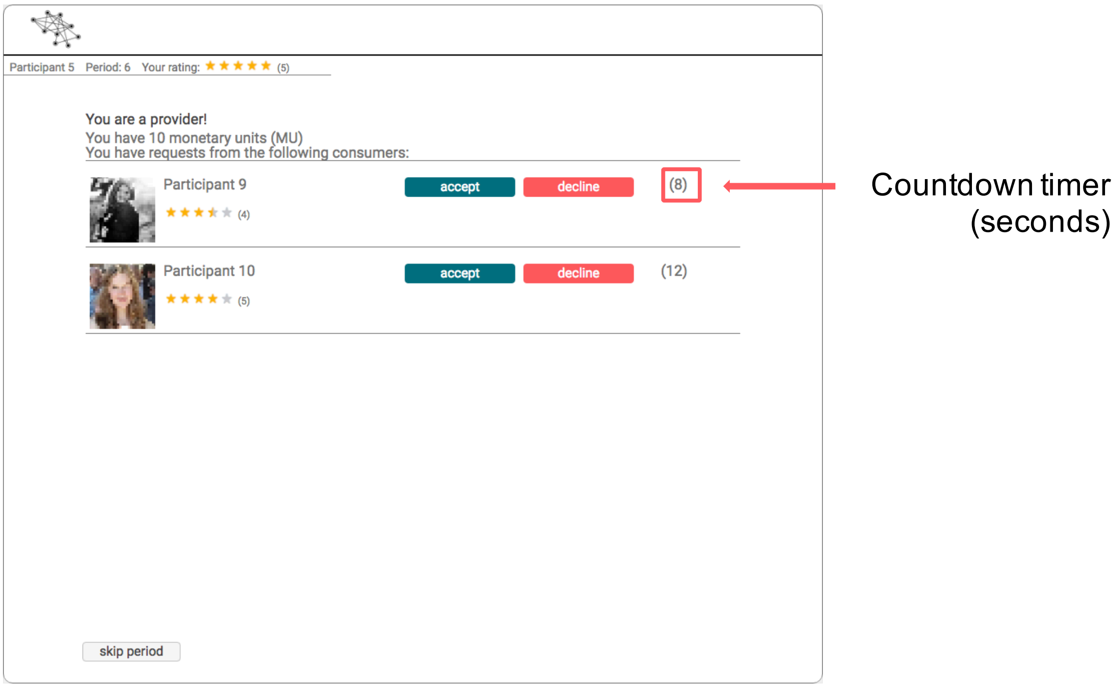

Figure C.20: Request countdown

If you accept one of multiple open requests, all others are automatically declined. The consumer whose request you have accepted is your transaction partner for the second phase of this period. The consumer will send you a 5 MU booking fee that will be added to your endowment for this period. The "continue" button brings you to the second phase of this period.

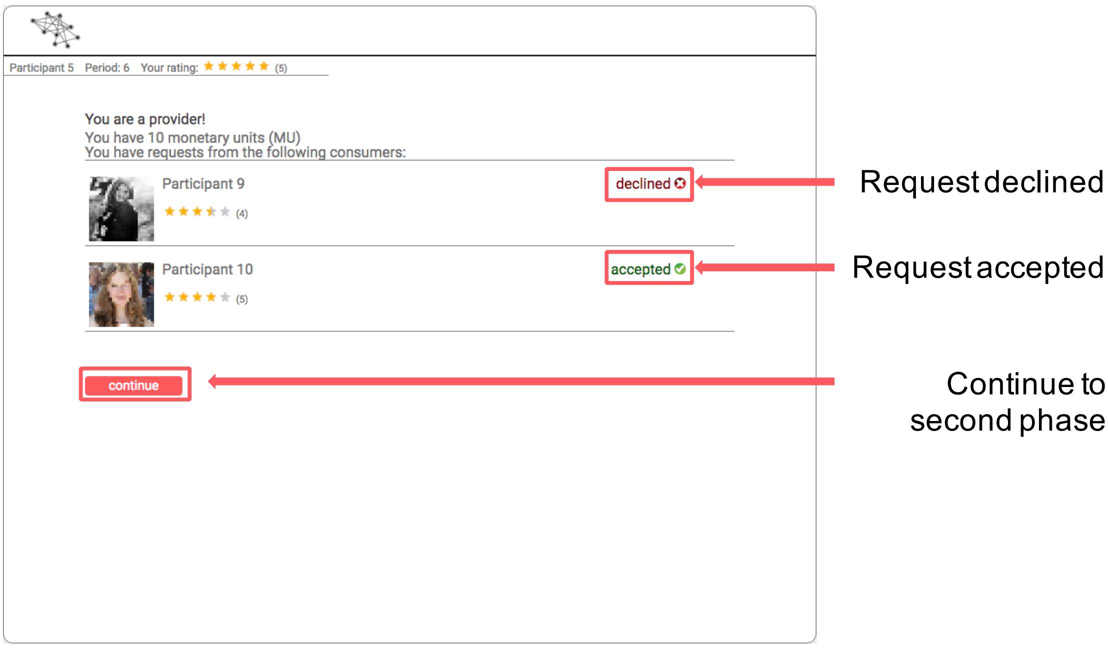

Figure C.21: Accepted request

If you do not receive any requests in the current period, or if you have rejected all requests received, you will not participate in the second phase of this period. The "continue" button brings you directly to the period summary. Your payoff for this period will be your endowment (10 MU).

Figure C.22: No consumer requests

Second Phase (Provider)

In the second phase of a period, you must now decide how much of your endowment you want to transfer to your transaction partner via a dropdown bar. This amount will then be subtracted from your endowment for this period. It is then multiplied by a factor of 3 and added to the consumer's account. Confirm your choice by clicking the "continue" button.

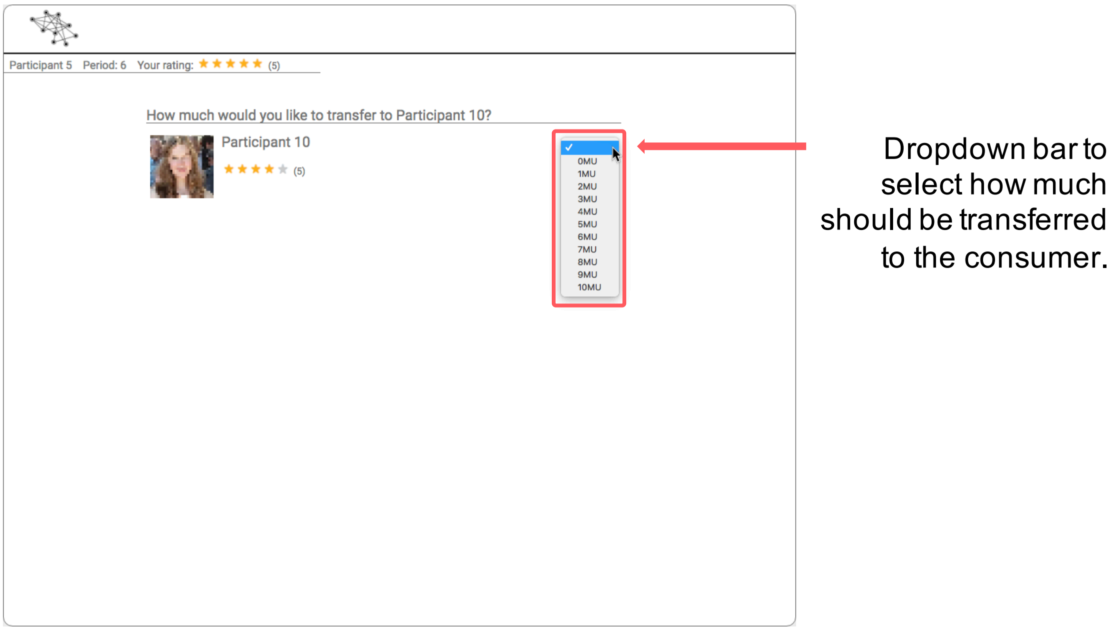

Figure C.23: Transfer to consumer

Once the consumer has received the tripled amount of what you have transferred, your transaction partner can now decide to transfer an amount back to you. This amount will be credited to your payoff of this period (without further tripling). A waiting screen is displayed during this transaction.

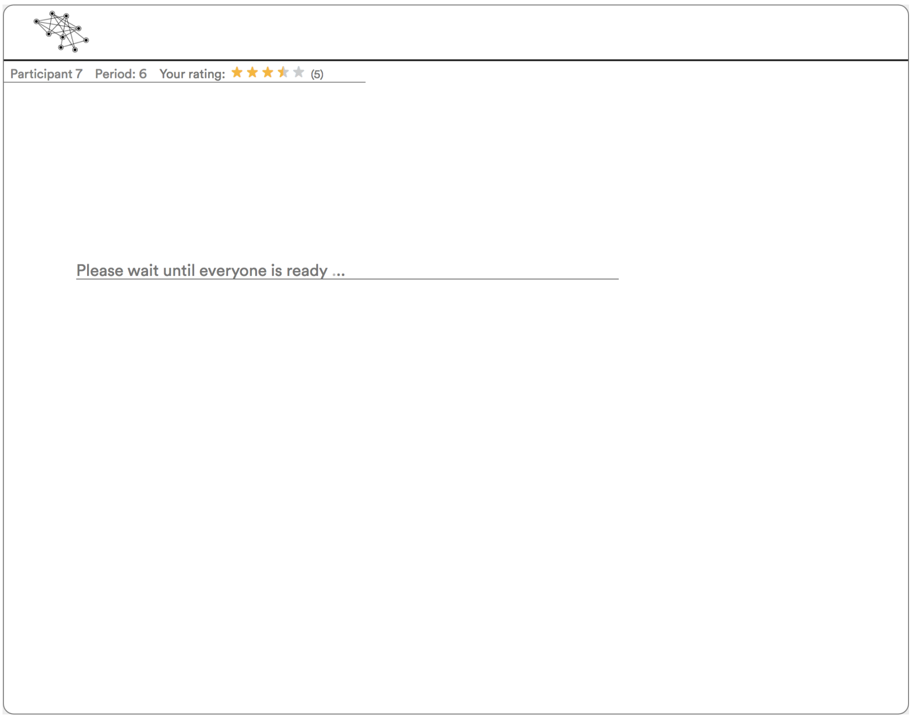

Figure C.24: Waiting screen

Period Summary (Provider)

Once your transaction partner has transferred an amount back to you, the period summary will be displayed. The period summary will show you your payoff for this period. Using the five-star rating system, you must evaluate your partner for this transaction. You will also receive a rating for this period from your transaction partner. Confirming your rating with the "continue" button brings you to the first phase of the next period.

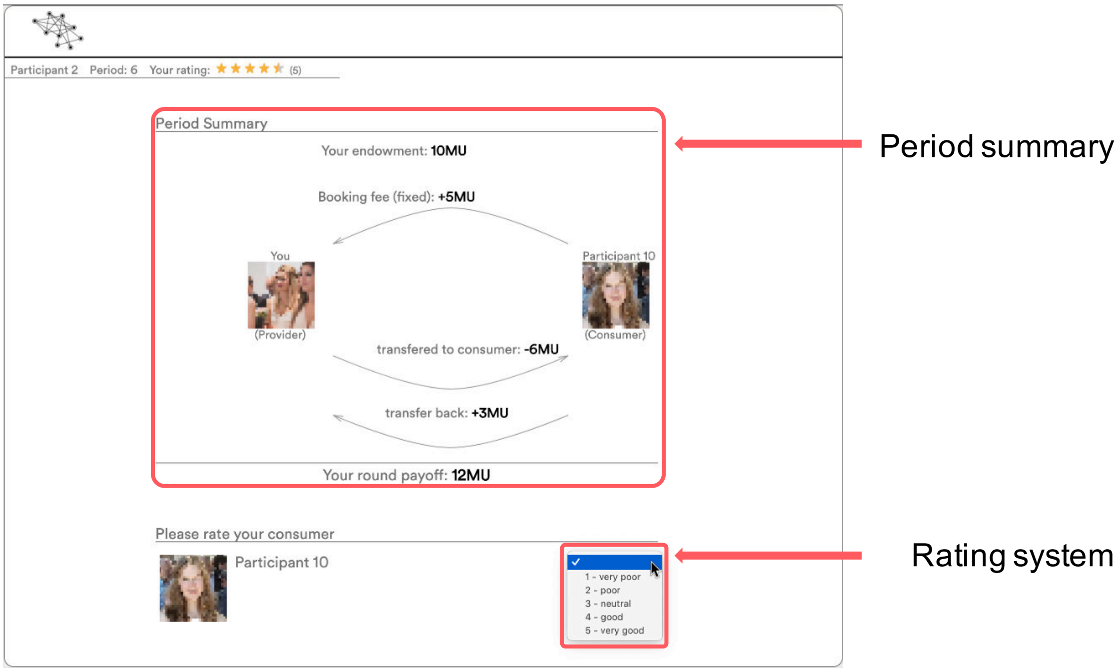

Figure C.25: Period summary (provider)

Comprehension Questions (Provider)

With the following questions you can check whether you have understood the rules of this experiment. The statements are either true or false. Please check the correct answer.

		True	False
1.	At the beginning of each period my endowment is 10 MU.	O	O
2.	I am assigned the same interaction partner in each period.	O	O
3.	If I reject a consumer's request, I will not receive any further requests in this period.	O	O
4.	If I don't have an interaction partner in a period, my payoff for that period is 10 MU.	O	O
5.	My final payoff in € at the end of the experiment depends on the results of my periods.	O	O
6.	If I accept the request of a consumer, I receive a booking fee of 5 MU.	O	O

Figure C.26: Comprehension questions (provider)

C.7 Manipulation Check Material

Table C.12: Manipulation check constructs and items

Construct	Code	Item
Cognitive Trust (COG)	MC_COG_1	The interface allows me to assess the other user based on a star rating score.
	MC_COG_2	The interface allows to draw trust inferences about the other user based on a numerical assessment of their past behavior.
	MC_COG_3	The interface allows me to make an analytical assessment about the other user's trustworthiness.
	MC_COG_4	The interface allows for a cognitive assessment of the other user's trustworthiness.
Affective Trust (AFF)	MC_AFF_1	The interface allows me to assess the other user based on a profile image.
	MC_AFF_2	The interface allows me to draw trust inferences about the other user by literally "seeing it in their faces".
	MC_AFF_3	The interface allows me to emotionally evaluate the other user's trustworthiness.
	MC_AFF_4	The interface allows for an affective assessment of the other user's trustworthiness.

C.8 Focus of this study

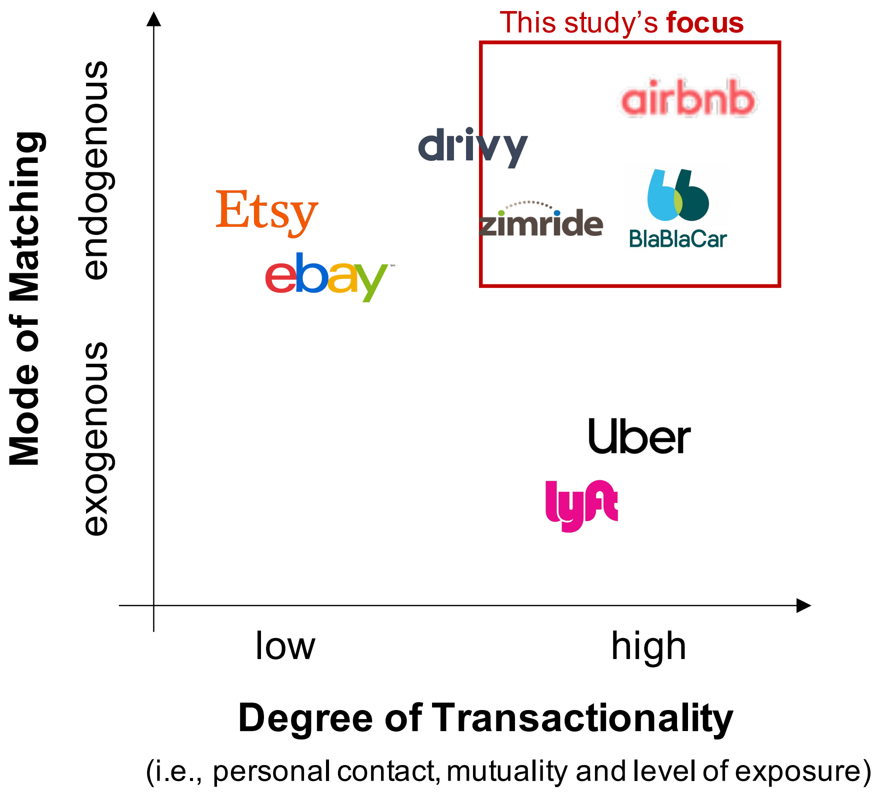

Figure C.27: Delineation of platform businesses by mode of matching and transactionality

D Supplementary Material for Chapter 3.3

Table D.13: Applied measurement scales in the research model and outer loadings

Construct	Code	Items (adapted)	loading/ weight
Trust in Blockchain *(formative)* Söllner, Hoffmann, and Leimeister (2016)	TBL1	I feel good about how things go when doing activities on the Blockchain.	.543
	TBL2	I feel assured that legal and technological structures adequately protect me from problems on the Blockchain.	.653
Trust in Blockchain User *(formative)* Söllner, Hoffmann, and Leimeister (2016)	TBU1	Information provided by other users of the Blockchain is valuable. (dropped)	.145†
	TBU2	Other users of the Blockchain offer me help when I have questions.	.341
	TBU3	In general, I can count on the information provided by other Blockchain users.	.859
Trust in Platform *(reflective)* Möhlmann and Geissinger (2018)	TPL1	As a platform provider, Slock.it can be trusted at all times.	.756
	TPL2	As a platform provider, Slock.it can be counted on to do what is right.	.805
	TPL3	As a platform provider, Slock.it has high integrity.	.834
	TPL4	Slock.it is a competent platform provider.	.826
Trust in Peers *(reflective)* Möhlmann and Geissinger (2018)	TPE1	The peers on the Slock.it platform are in general dependable.	.611
	TPE2	The peers on the Slock.it platform are in general reliable.	.852
	TPE3	The peers on the Slock.it platform are in general honest.	.825
	TPE4	The peers on the Slock.it platform are in general trustworthy.	.880
Trust in Product *(reflective)* Hawlitschek, Teubner, and Weinhardt (2016)	TPR1	In general, the products on the Slock.it platform will fulfill their tasks reliably.	.812
	TPR2	In general, you will rarely experience nasty surprises with the products on the Slock.it platform.	.683
	TPR3	In general, the products booked on the Slock.it platform will not break down during use.	.684
	TPR4	In general, the products on the Slock.it platform will not have defective parts.	.741
Intention to Rent *(reflective)* Lu, Zhao, and Wang (2010)	INR1	Given the chance, I would consider renting products from the Slock.it platform in the future.	.930
	INR2	It is likely that I will actually rent products on the Slock.it platform in the near future.	.879
	INR3	Given the opportunity, I intend to rent products on the Slock.it platform.	.940

Note: † initial loading for items removed in the course of measurement model evaluation.

E Supplementary Material for Chapter 3.4

Table E.14: Constructs, Items, and Sources

Code	Construct	Original Item	Adaption	Reference
ITB1	Purchasing Intentions	I am very likely to buy ticket from Travelocity.com.	I would be very likely to book at the selected provider.	Gefen and Straub (2003)
ITB2		I would use my credit card to purchase from Travelocity.com.	I would stay at the selected provider's apartment.	
ITB3		I would not hesitate to provide information about my habits to Travelocity.	I would not hesitate to request a booking with the selected provider.	
MN1	Moral Norms	It is my moral obligation to other people and/or the environment that I recycle my waste in the Blue Bins	It is my moral obligation to other people and/or the society that I book at providers that pay their taxes.	Botetzagias, Dima, and Malesios (2015)
MN2		It is morally responsible to other people and/or the environment that I recycle my waste in the Blue Bins	It is morally responsible to other people and/or the society to book at providers that pay their taxes.	
MN3			I would have moral scruples to book at providers that do not pay their taxes.	own
TIP1	Trust in Provider	As an auction host/intermediary, Amazon can be trusted at all times.	The selected listing's provider can be trusted.	Pavlou and Gefen (2004)
TIP2		As an auction host/intermediary, Amazon can be counted on to do what is right.	The selected listing's provider can be counted on to do what is right.	
TIP3		As an auction host/intermediary, Amazon has high integrity.	The selected listing's provider has high integrity.	
TIP4		Amazon is a competent and knowledgeable auction host/intermediary.	The selected listing's provider is competent and knowledgeable.	

Table E.15: Demographic and Control constructs, Manipulation Check Items, and Sources.

Code	Construct	Original Item	Adaption	Reference
DTT1	Trusting Disposition	I generally trust other people	I generally trust other people.	Gefen and Straub (2004)
DTT2		I tend to count upon other people	I tend to count upon other people.	
DTT3		I generally have faith in humanity	I generally have faith in humanity.	
DTT4		I feel that people are generally well meaning	I feel that people are generally well meaning.	
DTT5		I feel that people are generally trustworthy	I feel that people are generally trustworthy.	
DTT6		I feel that people are generally reliable	I feel that people are generally reliable.	
FAM1	Familiarity	I am familiar with searching for books on the Internet	I am familiar with searching for apartments on the Internet.	Gefen and Straub (2004)
FAM2		I am familiar with buying books on the Internet	I am familiar with renting apartments on the Internet.	
FAM3		I am familiar with Amazon.com	I am familiar with platforms such as Airbnb, Homestay, 9flats, or or similar.	
FAM4		I am familiar with inquiring about book ratings at Amazon.com	I am familiar inquiring about apartment and provider ratings at Airbnb, Homestay, 9flats, or similar.	
MC1	Manipulation Check Label		I am confident the selected provider is paying taxes for renting the apartment.	own
MC2	Manipulation Check Price		I perceive this apartment to be relatively expensive.	own
CTR1	Control Question		Please check the second box from the left.	own

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(3. Nicht zutreffend.)

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6. In die Dissertation wurden Vorveröffentlichungen und zur Veröffentlichung eingereichten Arbeiten einbezogen, bei denen ich im Rahmen einer Mitautorenschaft jeweils einen signifikanten Teil selbstständig erbracht habe. Eine Aufstellung mit den Angaben:

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David Dann

Anlage: Aufstellung der Vorveröffentlichungen und zur Veröffentlichung eingereichten Arbeiten

Autoren/Autorinnen:	Dann, D., Teubner, T., Weinhardt C.
Titel der Vorveröffentlichung:	Poster child and guinea pig – insights from a structured literature review on Airbnb
Veröffentlicht in:	International Journal of Contemporary Hospitality Management (2019) 31.1, pp. 427–473.

Autoren/Autorinnen:	Dann, D., Teubner, T., Adam, M. T. P., Weinhardt, C.
Titel der Vorveröffentlichung:	Where the host is part of the deal: Social and economic value in the platform economy
Veröffentlicht in:	Electronic Commerce Research and Applications (2020) 40.1, pp. 1–12

Autoren/Autorinnen:	Dann, D., Teubner, T., Möhlmann, M., Hawlitschek, F., Adam, M. T. P.
Titel der Vorveröffentlichung:	On the dynamics of cognitive and affective trust cues: Behavioral evidence from a peer-to-peer sharing platform experiment
Veröffentlicht in:	Working Paper (Submitted to Journal of the Association for Information Systems)

Autoren/Autorinnen:	Dann, D., Hawlitschek, F., Peukert, C., Martin, C., Weinhardt, C.
Titel der Vorveröffentlichung:	Blockchain and Trust in the Platform Economy: The Case of Peer-to-Peer Sharing
Veröffentlicht in:	WI 2020 Proceedings, pp. 1459–1473

Autoren/Autorinnen:	Dann, D., Müller, R., Werner, A., Mädche, A., Spengel, C.
Titel der Vorveröffentlichung:	How do Tax Compliance Labels Impact Sharing Platform Consumers? An Empirical Study on the Interplay of Trust, Moral, and Intention to Book
Veröffentlicht in:	Working Paper (Submitted to Business & Information Systems Engineering)