



**HAL**  
open science

# The role of legitimacy and reputation judgments in users' selection of service providers on sharing economy platforms

Yann Truong, Claire-Lise Ackermann, Richard Klink

► **To cite this version:**

Yann Truong, Claire-Lise Ackermann, Richard Klink. The role of legitimacy and reputation judgments in users' selection of service providers on sharing economy platforms. *Information and Management*, 2021, 58 (8), pp.103529. 10.1016/j.im.2021.103529 . hal-03412788

**HAL Id: hal-03412788**

**<https://rennes-sb.hal.science/hal-03412788>**

Submitted on 16 Oct 2023

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

# **The Role of Legitimacy and Reputation Judgments in Users' Selection of Service Providers on Sharing Economy Platforms**

**Dr Yann Truong\***

**Professor of Digital Management**

CEREN, EA 7477

Burgundy School of Business

Université Bourgogne Franche-Comté

29 Rue Sambin

21000 Dijon

France

Yann.truong@bsb-education.com

Tel: +33 (0) 3 80 72 59 00

**Dr. Claire-Lise Ackermann**

**Associate Professor of Marketing**

Rennes School of Business

2 rue Robert D'Arbrissel

35000 Rennes

claire-lise.ackermann@rennes-sb.com

Tel : +33 (0) 2 99 54 63 63

**Richard R. Klink**

**Professor of Marketing**

The Sellinger School of Business

Loyola University Maryland

4501 North Charles Street

Baltimore, MD 21210-2699 USA

TEL: 410-617-5546

FAX: 410-617-2117

rklink@loyola.edu

## **ASBTRACT**

Information systems literature suggests that reputation is the main judgment form that captures user-related information online. Drawing on social judgment literature, we contend that a user's online characteristics and past actions are not all reputation-based, but also legitimacy-based, and that transaction stake determines whether users will use reputation or legitimacy judgment to evaluate other users. Using Airbnb, we show that level of stake in a transaction determines the judgment form (reputation or legitimacy) that guests resort to when evaluating a host. Moreover, we find that providing extensive information on a host to potential guests in low-stake transactions is counterproductive.

**Keywords:** Sharing economy, platform, social judgment, legitimacy, reputation

## 1. INTRODUCTION

Sharing economy reflects a critical digital innovation; companies taking advantage of this innovation use online platforms to connect parties with underused assets with others who seek to rent those assets temporarily (Cusumano, 2015; Lee, Lee, & Kim, 2019). Such companies supply various goods and services, including peer-to-peer (P2P) lending (e.g., Kickstarter), food delivery (Uber Eats), transportation (Uber), accommodations (Airbnb), and catering (Feastly). According to a McKinsey report, revenues generated by the sharing economy are projected to reach US\$335 billion globally by 2025 (Marchi & Parekh, 2015).

Despite the impressive growth potential of this market, more research is needed to unravel the mechanisms underlying user exchanges on sharing economy platforms. While recent studies have improved our understanding of the criteria that explain why individuals use sharing economy platforms (e.g., booking a room on Airbnb) rather than their traditional economy counterparts (e.g., booking an hotel room) (Belk, 2014; Mahadevan, 2018; Möhlmann, 2015; Scaraboto, 2015), little is known about users' decision-making process on sharing economy platforms (Yang, Lee, Lee, & Koo, 2018). Indeed, a characterizing premise of the sharing economy is that users must trust complete strangers who let them enter into their intimacy (Ert, Fleischer, & Magen, 2016), such as their personal car and spare rooms. Therefore, it is of critical importance to both researchers and sharing platforms to understand how users select trustworthy service providers on sharing economy platforms. Selection task is particularly challenging for both users and platforms as the large number of members and the unlikeliness of repeated transactions with a particular member create an environment of persistent information asymmetry between users and service providers. Consequently, sharing economy platforms provide an array of information, mostly consisting of service provider profiles, ratings, and detailed reviews of past users, to accompany users in the potentially complex

selection task. However, we do not know much about how users build on this information to make decisions, which limits the possibility of streamlining the way platforms provide relevant information based on the need of users. Disentangling the mechanisms that underlie selection task on these platforms is an important topic because sharing economy companies need to design platforms that reduce the level of complexity in the decision-making process to build trust on the platform and increase use.

In information systems literature, reputation may reflect all that is said about a person (Jøsang, Ismail, & Boyd, 2007) or one's past actions within a community (Dellarocas, 2010; Li, Fang, Lim, & Wang, 2019), and is the main lens through which a community member's trustworthiness is evaluated (Chang, Cheung, & Tang, 2013; Huang, Davison, & Liu, 2014; Jones & Leonard, 2008; Jøsang et al., 2007; Ye, Gao, & Viswanathan, 2014; Ye, Viswanathan, & Hann, 2018). For example, Dellarocas (2010) proposes that community members use reputation information, such as profiles, ratings, activity statistics, scores, reviews, and past behaviors to assess the level of trust of another member before engaging in a collaboration or a transaction. However, recent development in the literature on social judgment suggests that reputation is not the sole judgment form that people use to evaluate the trustworthiness of another individual or entity. In their examination of how evaluators form and use social judgments in the process of selecting an exchange partner under conditions of bounded rationality, organizational scholars have identified two important forms of social judgment that affect evaluators' selection decision: legitimacy and reputation (Bitektine, 2011; Deephouse & Carter, 2005). Distinguishing between these two forms is critical because reputation judgment evaluates a partner at the individual level (is this partner reliable?) while legitimacy judgment evaluates a partner at the category level (is this partner appropriate?). Therefore, they involve levels of cognitive effort and processes that vary depending on transaction stake (Bitektine, 2011). The objective of this research is to demonstrate that

member-related information on sharing economy platforms may be used to form not only reputation judgments, but also legitimacy judgments. Through a series of empirical studies, we attempt to show that users on sharing economy platforms form both reputation and legitimacy judgments when selecting an exchange partner and that the level of stakes in a transaction determines the form of judgment they employ. We focus on level of stake as the literature on social judgment formation posits that the level of stake in a transaction is a critical determinant of the form of judgment to be used in decision-making (Bitektine, 2011; Deephouse & Carter, 2005; King & Whetten, 2008).

Our research makes important contributions to the literature on reputation on online market platforms. First, information systems literature suggests that all the information about a member (e.g., profiles, ratings, activity statistics, scores, reviews, past behaviors) is related to reputation (Dellarocas, 2010; Zervas, Proserpio, & Byers, 2015), assuming that users activate only one cognitive process when they select an exchange partner. Using social judgments in this research allows us to differentiate the forms of judgment at play in users' selection process. Specifically, the literature on social judgments enables us to link information cues to distinct forms of judgment beyond reputation to include legitimacy as a valid form of judgment for exchange partner selection. In distinguishing the two judgment forms (reputation and legitimacy), we attempt to show that users activate distinct cognitive processes depending on which form they employ in partner selection tasks. Second, the influence of stake as a determinant of user involvement in the selection process, and thus, the judgment form to be used, is a hallmark of social judgment literature. The current literature has not fully examined how level of user motivation affects the processes of judgment formation in exchange partner selection task. Therefore, using social judgments in our research enriches our understanding of information cues and judgment forms, and emphasizes the role of stake in influencing the cognitive processes of judgment formation in users'

selection task. Finally, we add to the literature by focusing on sharing economy platforms. Current work in the field is mostly limited to conceptualization (Belk, 2014; Guyader, 2018; Kumar, Lahiri, & Dogan, 2018; Perren & Kozinets, 2018), usage motivation and intention (Mahadevan, 2018; Möhlmann, 2015) macro-level impacts and regulation (Jordan & Moore, 2018; Prayag & Ozanne, 2018), and the economics of collaboration (Scaraboto, 2015; Weber, 2014; Zervas, Proserpio, & Byers, 2017). Our review of the literature reveals a lack of understanding of how users select service providers, even though selection task is a critical behavioral component of the decision-making process. In this study, we attempt to unravel some of the mechanisms of users' selection decision.

## **2. CONCEPTUAL BACKGROUND**

### **2.1 Sharing Economy**

The sharing economy focuses on the provision of services with an individual's own assets (Lee, Yang, & Koo, 2019). Though web-based platforms are not a necessary condition for enabling such practices (e.g., offline toy libraries enable parents to share communally owned toys in their neighborhood (Ozanne & Ballantine, 2010), Web 2.0 technologies are at the heart of the astounding development of the phenomenon worldwide (Belk, 2014; Parguel, Lunardo, & Benoit-Moreau, 2017; Yang & Mao, 2019). Thus, sharing economy may be viewed as “a two-sided market model that allows private individuals to share resources with potential customers through an online platform in the form of temporary access to goods and services without transferring permanent ownership” (Mittendorf, Berente, & Holten, 2019, p. 1085).

Since sharing economy platforms are dramatically altering existing markets by offering innovative, convenient, and cost-efficient services that challenge incumbent service providers in mature industries (Dogru, Mody, Suess, McGinley, & Line, 2020; Leung, Xue, & Wen, 2019; Muñoz & Cohen, 2017), they have drawn scholars from different disciplines into an

emerging research area (Sutherland & Jarrahi, 2018). Research has initially focused on the understanding of the sharing economy as a phenomenon (Belk, 2014; Chasin, von Hoffen, Cramer, & Matzner, 2018; Guyader, 2018; Kumar et al., 2018; Möhlmann, 2015; Perren & Kozinets, 2018), with some scholars who consider it as an umbrella construct encompassing very heterogeneous non-market and market practices and sectors (Acquier, Carbone, & Massé, 2016). The growing literature has mainly investigated the economics of collaboration (Scaraboto, 2015; Weber, 2016; Zervas et al., 2017) and its macro-level impacts and regulation (Jordan & Moore, 2018; Prayag & Ozanne, 2018). For example, Greenwood and Wattal (2017) study the societal benefits of sharing economy platforms and find that the introduction of ride-sharing (i.e., Uber X) in California resulted in increased availability of transportation services and, when coupled with cost savings, led to a significant drop in the rate of motor vehicle fatalities. Using Airbnb as a field of investigation, Gibbs et al. (2018) find that physical characteristics, location, and host characteristics have an impact on price. Less attention, however, has been paid to the consumption aspects of sharing economy.

From a consumption point of view, a first important emerging theme in sharing economy research concerns users' sources of motivation. It has been initially argued that the rise of the sharing economy is driven by both societal and economic considerations (Ert, Fleischer, & Magen, 2016). However, although prior research on sharing practices suggests that values such as community building and anti-consumption can explain motivations to share goods with other consumers (Ozanne & Ballantine, 2010), societal motivations do not seem to drive the use of sharing economy platforms; rather, cost saving and utility seem to be the main drivers of consumption on these platforms (Möhlmann, 2015). For example, a survey conducted among 168 registered users of a sharing economy platform (i.e., Sharetribe) showed that viewing the sharing economy as a sustainable mode of consumption has a positive effect on consumers' evaluation of this form of consumption but does not translate



strongly into behavioral intention; conversely, whereas anticipated economic gains do not have a positive effect on consumers' evaluation of this form of consumption, they strongly predict behavioral intentions (Hamari, Sjöklint, & Ukkonen, 2016). To conclude, the use of sharing economy services seems to be predominantly driven by rational motivations, serving users' self-benefit.

A second important emerging theme in the literature on consumption aspects of the sharing economy concerns trust. Trust is a psychological state (Chang et al., 2013) and may be defined as "an expectancy held by an individual or a group that a word, promise, verbal or written statement of another individual or group can be relied upon" (Rotter, 1967, p. 651). It can play a key role in electronic markets that involve high uncertainty and sometimes a lack of legal protection (Luo, 2002). Research has found that trust is an essential determinant of usage of sharing economy platforms (Mahadevan, 2018; Möhlmann, 2015; Perren & Kozinets, 2018). Interpersonal trust has also been identified as an important aspect of sharing economy relationships in the accommodation sector (Prayag & Ozanne, 2018). Using the case of Airbnb, Yang et al. (2018) have explored how available information (e.g., reviews, introduction message, informative pictures, etc.) contribute to building credibility and emotional bonding, which in turn affect trust in the service provider (i.e., interpersonal trust) and trust in the brand. Cheng et al. (2019) have more specifically investigated which aspects of online reviews are used by guests to infer hosts' trustworthiness on AirBnb. Others have investigated how information provided by the hosts (e.g., self-description and photo) contribute to building trust among traders (Ert et al., 2016; Tussyadiah & Park, 2018). Zhang et al. (2018) identify ratings and reviews as antecedents of reputation, and show that reputation plays a critical role in building trust.

The literature on the sharing economy has extensively focused on understanding which factors may determine consumers' adoption of sharing economy platforms (i.e., societal

considerations, economic gains, trust in the platform). However, it has paid less attention to how users on a trusted sharing economy platform chose between different service providers. The specificity of the sharing economy is that users must choose not only between different platforms (e.g., Airbnb or FlipKey, Uber or Lyft), but also between different services providers on each platform. So far, little attention has been paid to how users evaluate and select service providers on sharing economy platforms. Most studies have examined interpersonal trust and its antecedents (Cheng et al., 2019; Ert, Fleischer, & Magen, 2016; Tussyadiah & Park, 2018; Yang et al., 2018; Zhang, Yan, & Zhang, 2018). Reputation, enabled by reputation mechanisms (based on reviews) has often been identified as the most important antecedent of trust (Zhang, Yan, & Zhang, 2018). Past research has mostly investigated how users process available information on sharing economy platforms in a fragmented way, by investigating one specific aspect (e.g., traveler vs. worker host profile, Tussyadiah & Park, 2018), but what is needed is a more comprehensive approach to eliciting users' information processing on sharing economy platforms (Yang et al., 2018). In addition, by extensively focusing on reputation, past research has neglected other forms of judgment that users may resort to in their evaluation of a service provider on a sharing economy platform.

## **2.2 Information on Sharing Economy Platforms**

The role of sharing platforms is not only to connect suppliers and consumers, but also to help them make the “right” decision. In this perspective, sharing platforms have developed and implemented a sophisticated series of mechanisms and algorithms inspired by the rating and review systems pioneered by e-commerce companies to facilitate consumers' access to relevant information about a product or provider. The most popular sharing platforms often provide three forms of information to users: (1) profiles of service providers (i.e., labels or

badges indicating the category to which they belong or validation of a set of personal data), (2) ratings of service providers by past users, and (3) detailed reviews of past users.

Profile information typically includes a set of personal data provided by service providers (e.g., photo, email address, physical address). Some platforms have also developed a system of labels or badges summarizing this profile information. For example, on BlaBlaCar, service providers belong to one of four categories (intermediate, experienced, expert, and ambassador) that indicate the extent to which they are considered a “trusted member of the BlaBlaCar community.” The criteria platforms use to differentiate the categories are email and mobile number verification, profile completion by the service provider, number and percentage of positive ratings, and membership date.

Beyond the profile information, sharing platforms encourage users to rate and leave a written comment of their experiences with service providers after the service has taken place. Sharing platforms stress that the purpose of ratings and evaluation systems is to help users build trust in service providers. Indeed, the section on “Trust and Safety” on Airbnb states, “To help keep our community safe and trusted, we’ve published our standards and expectations for all hosts and travelers”<sup>1</sup>; statements on BlaBlaCar stipulate that “all profiles, photos, ratings, ride offers and ride comments are moderated to maintain trust and respect in the community.”<sup>2</sup>

However, while sharing platforms have extensively developed different types of information to improve trust between users and service providers, little is known about how users make use of this information to select appropriate service providers. In this research, we draw on social judgment literature to contend that the process of evaluating service providers on sharing economy platforms involves the formation of both legitimacy and reputation judgments, as discussed in the next section.

---

<sup>1</sup> <https://www.airbnb.com/help/article/1199/what-are-airbnb-s-standards-and-expectations?locale=en>, accessed February 22, 2019.

<sup>2</sup> <https://www.blablacar.co.uk/trust-safety-insurance>, accessed February 22, 2019.

## **2.3 Legitimacy and Reputation as Social Judgments**

Social judgment is concerned with the question of how individuals perceive and evaluate an idea by comparing it with current attitudes (Sherif & Hovland, 1961). In the organizational literature, Bitektine (2011) defines social judgment as an evaluator's decision or opinion about the social properties of an organization. Social judgments involve analytical processing of different aspects of organizations (e.g., product quality, size, and other organizational characteristics) by social actors who interact with them. The author further explains the process of judgment formation by recognizing the importance of active cognitive processing and information search efforts that precede the formation of different forms of social judgments. Simply put, in the context of our research, social judgment may be viewed as users' evaluation of the social properties of a service provider in their selection task, and that the outcome of the selection process is a social judgment. Specifically, we focus on two forms of judgment that are most relevant to explain how users build on the information available on platforms to form judgments about service providers, namely, legitimacy and reputation. The literature has often considered that the two forms of judgment play a significant role in explaining the choice of exchange partners in business transactions (Bitektine, 2011; Deephouse & Carter, 2005).

### **2.3.1 Legitimacy**

Suchman (1995, p. 574) defines legitimacy as a generalized perception of organizational actions as “desirable, proper or appropriate within some socially constructed system of norms, values, beliefs and definitions.” As such, aligning an organization's behavior with a community's social systems is necessary to gain legitimacy (Scott, 1995). By conferring legitimacy to organizations, social actors promote organizations they perceive as beneficial to them, their social group, or society as a whole (Bitektine, 2011). As a legitimate organization is endorsed and supported by its constituencies, its existence and right to conduct business is

unchallenged within the community in which it is embedded (Ahlstrom & Bruton, 2001).

Therefore, legitimacy is often considered a critical resource for both resource acquisition and survival, especially at the early stage of an organization's existence (Zimmerman & Zeitz, 2002).

Although extant literature suggests many dimensions of legitimacy, prior studies have mostly investigated cognitive and socio-political legitimacy (Aldrich & Fiol, 1994), moral and pragmatic legitimacy (Suchman, 1995), and normative and regulative legitimacy (Scott, 1995). The multiple dimensions of legitimacy are not mutually exclusive; rather, they often overlap, as conformance to one dimension will potentially affect the others. Assuming that legitimacy is additive rather than zero-sum (Kraatz & Block, 2008), we adopt Tost's (2011) approach to employing a generalized form of legitimacy to represent an evaluator's general perception of the appropriateness of an entity; here, an entity is represented as either appropriate or inappropriate within its social context. In the case of sharing economy platforms, we view legitimate service providers as those who conform to the platform community's rules and norms such that their existence and right to provide services is unquestioned.

The literature states that an actor is granted legitimacy by the community through conformance to familiar and comprehensible structures (cognitive), norms and values (normative), and laws and legislations (regulative) (Scott, 2013). On sharing platforms, cognitive legitimacy may be achieved when a member fits the profile that is typically expected by other members on the platform for a particular service (Tseng & Chan, 2019). For example, Uber drivers may upload photos of them in formal dressing as riders would expect them to look like chauffeurs. By looking like a chauffeur, a Uber driver appeals to a familiar cognitive frame in the mind of riders (Mair & Reischauer, 2017). Normative legitimacy refers to what a community considers as appropriate or normal practices on the

platform (Gonzalez-Padron, 2017). Conforming to a platform's code of conduct or service standards (Gonzalez-Padron, 2017) may grant normative legitimacy, for instance, Airbnb expects hosts to be honest about the characteristics of the rental and to offer clean apartments to guests. Finally, regulative legitimacy is conferred when a member obeys to the laws of a country or the rules of the platform (Uzunca, Rigtering, & Ozcan, 2018). Uber states that it may ban drivers who request to be paid in cash rather than using its payment system.

### ***2.3.2 Reputation***

Reputation refers to “a set of attributes inferred from the firm's past actions and ascribed to the firm” (Weigelt & Camerer, 1988, p. 454). From an economic perspective, emphasis is on the organization's ability to deliver value superior to that of its competitors (Rindova, Williamson, Petkova, & Sever, 2005). Reputation comprises a set of unique organizational attributes that can be inferred from an organization's past. As such, this social judgment can be used to predict the future behavior of the organization (e.g., it has a reputation for cutting prices, being honest, being reliable) (Bitektine, 2011).

On sharing economy platforms, online reputation has become a major source of trust between users who often do not know each other, given the unlikelihood of repeated transactions between users and a particular service provider (Tadelis, 2016; Zervas et al., 2015).

Therefore, online platforms have developed feedback and review systems to temper the severity of asymmetric information and the likelihood of opportunistic behavior (Huang et al., 2014; Tadelis, 2016) by encouraging past users to rate products, services, and providers.

As reputation is formed on the basis of past actions, a member's reputation tends to result from her/his history of performance or behavior on the platform. On sharing platforms, information about a member's past performance and behavior are often reported by other members in their reviews or feedbacks (Zervas et al., 2015). Such a review or feedback

system has a large influence on members' behavior. For instance, Uber drivers would want to be courteous to riders to obtain a positive feedback so future riders select them, and in turn, riders would want to return the same courtesy as drivers are allowed to not accept riders with negative feedbacks (Moon, 2015). As members are encouraged to post feedback of their experience, they tend to report specific and sometimes detailed behaviors of the member being rated (Cui, Li, & Zhang, 2020). The more frequently a specific behavior is reported in a review, the more it is seen as being diagnostic of a member (Mishina, Block, & Mannor, 2012; Prabhu & Stewart, 2001), for example, passengers on BlaBlaCar may report that a particular driver is talkative or safe-driving minded (Guyader, 2018). Therefore, the more a member exhibits a particular behavior, the more past members are likely to report such behavior, so that the evaluated member will develop a reputation for such behavior. On BlaBlaCar, driving safely (or not) in a consistent manner will earn the driver a reputation of being a safe driver (or not). It is also expected that a member will proactively exhibit a behavior that is highly distinctive and valuable on the platform such as cleanliness for Airbnb rentals. On Airbnb, offering consistently clean apartments to guests will confer to the host a reputation for clean rentals through the reviews and ratings. Reputation scholars tend to suggest that one does not have an overall and general reputation but a reputation for something (Bitektine, 2011; Lange, Lee, & Dai, 2011; Prabhu & Stewart, 2001), and thus, it is the repetition of a particular behavior over time that leads to a reputation for such behavior.

The key difference between legitimacy and reputation depends on the perspective of the dimensions on which judgments are formed. Legitimacy is an assessment of an entity's conformance to a set of prevailing rules, norms, and cognitive expectations within a community or society, whereas reputation can be judged on any attribute with which entities can be compared (Deephouse & Carter, 2005). Consequently, the formation of legitimacy judgment and reputation judgment differs in the sense that the former (except for socio-

political legitimacy as this judgment involves the scrutiny of an entity's organizational features and performance against cultural norms and political authorities (Aldrich & Fiol, 1994) is mostly evaluated at the category level (industry, population, or group of companies or individuals) and focuses on similarities (e.g., a constituency confers legitimacy to an entity if it can categorize the entity as being a member of a group of similar entities), whereas the latter is evaluated at the entity's level (service provider or organization) and focuses on individual features: Under reputation judgment, an individual scrutinizes the specific behavioral attributes of the entity (Bitektine, 2011). The sets of dimensions forming legitimacy and reputation can overlap, even though the forms of judgment are fundamentally different (Bitektine, 2011). In summary, even if the criteria used to render legitimacy and reputation judgments overlap, the questions that the two forms of social judgment answer to are conceptually different: Legitimacy judgment is rendered when the evaluator needs to know whether the entity belongs to a category of familiar entities that are not problematic; reputation judgment is rendered when the evaluator needs to assess the entity's future behavior.

#### **2.4 Selection of Social Judgment Form**

In light of the previous discussion, the nature of the question the evaluator aims to answer regarding the focal entity dictates the selection of the form of judgment. Social judgment literature posits that the goal of the evaluator determines the form of judgment which, in turn, determines the information to be used to form the judgment. For instance, if an evaluator wants to take a taxi for a short trip, she or he may simply search for a legitimate taxi by identifying the name of a cab company that belongs to a group of familiar and non-problematic cab companies. Alternatively, if an evaluator wants to take a taxi for a long trip, she or he may want to search for a company that has a reputation for comfortable vehicles and reliable drivers.



Bitektine (2011) suggests that judgment forms may “compete” or be used concomitantly or sequentially. Taking the example of the selection of an exchange partner, he proposes that different forms of social judgment are used, and that the order in which they are used is a function of the cognitive efforts they require. Indeed, unlike feature-based judgments, category-based judgments help expedite decision processes (Yamauchi & Yu, 2008). Thus, as legitimacy judgments are category-based, they require less cognitive efforts than reputation judgments, which are feature-based. Therefore, under conditions of cognitive constraints, such as incomplete availability of information about the entity, time constraints, or limited attention, in selecting an exchange partner evaluators may use different forms of social judgment, such that the forms demanding the lowest level of cognitive effort precede those that are more demanding (Bitektine, 2011).

In addition, the level of motivation generated by the need to make the “right” judgment has an important effect on the intensity of the cognitive efforts that the evaluator will dedicate to the judgment. Well-established persuasion models (e.g., Heuristic-Systematic Model) (Chaiken, 1987) and Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986) identify motivation as a predictor of whether consumers will process information in a deliberate and systematic manner by thoroughly considering the message’s key arguments or, in a more incidental manner, by relying on peripheral cues or heuristics. Consumers tend to engage in heuristic or peripheral processing unless they are motivated to think carefully about information (Chaiken & Ledgerwood, 2011; Petty & Cacioppo, 1986). Thus, both the Heuristic-Systematic Model and the ELM would suggest that users on sharing economy platforms are more likely to use legitimacy judgments when economic stakes are low and to use reputation judgments when economic stakes are high: High motivation promotes extensive information search and careful consideration of the evaluative criteria, whereas low motivation favors the use of heuristics that can simplify and expedite decisions (Kruglanski,

2001). Therefore, evaluators are likely to use legitimacy judgments when economic stakes (including potential monetary losses and opportunity cost) are low because the impact of a “wrong” choice is minimal; conversely, they are likely to use reputation judgments when economic stakes are high as they are ready to expend greater efforts on due diligence, to avoid the consequences associated with a “wrong” choice, and thus attempt to resolve uncertainty about the future behavior of potential exchange partners from their past behavior and performance. Similar effects would be predicted by consumer involvement theory approach. Consumer involvement is a state of motivation, driven by different types of external variables, including the situation, and affecting information search, information processing, and decision-making (Rothschild, 1984; Zaichkowsky, 1994). Thus, the situation, that is, the level of stakes, is likely to determine the level of consumer involvement, which in turn influences motivation to search and process information. In a low-stake situation, consumer involvement is likely to be low, resulting in low motivation to search and process information, and increasing the likelihood that users will rely on a legitimacy judgment; in a high-stake situation, consumer involvement is likely to be high, resulting in high motivation to search and process information, and increasing the likelihood that users will rely on a reputation judgment. As a consequence, the level of stake of a transaction plays a critical role in determining the form of judgment that an individual will use in order to select an exchange partner.

## **2.5 Social Judgments in the Context of Sharing Economy Platforms**

In this study, we build on Bitektine’s (2011) framework of social judgment to investigate how users select service providers on sharing economy platforms. Although the concept of legitimacy has mostly been examined by institutional theorists in the context of organizations, it has also been employed in social psychology to explain the stability of and behavioral

reactions to a broader range of social entities, including individuals (Lawrence, 1998; Tost, 2011). Similarly, the concept of reputation has been examined in many contexts, including any type of individual or group (Mishina et al., 2012). Thus, we apply Bitektine's (2011) framework of social judgment to individuals in the context of sharing economy platforms. In this context, we view social judgment formation as users' evaluation of the social properties of a service provider within the decision-making process. In the sections below, we analyze the three different types of information available on sharing economy platforms and discuss how they may relate to legitimacy and reputation judgments.

## **2.6 Information Cues on Sharing Platforms**

Our research focuses on the case of Airbnb. The platform provides three types of information about service providers that are relatively representative of the practices of some of the largest platforms in other sectors (BlaBlaCar in carpooling, TaskRabbit in personal services, Couchsurfing in P2P lodging). Each type of information provides cues which may be used to form either legitimacy or reputation judgments depending on the evaluation goal, as discussed below

Profile: Hosts (those who offer rentals) are expected to provide a set of personal data to inform their profile (e.g., photo, email address, physical address, Facebook account, LinkedIn account, credit card number, work phone number). The data provided by service providers may vary in length and are visible on their profiles. As the list is institutionalized by the platform, the willingness to provide personal data for verification may be taken as signals of transparency and honesty; as the Airbnb website states: "Your profile is a great way for others to learn more about you before they book your space or host you. When your profile is robust, it helps others feel that you're reliable, authentic, and committed to the spirit of Airbnb." As the request emanates from the platform and not users, conforming hosts are endorsed by the platform, which certifies that the personal data are verified. This is similar to the notion of

regulative legitimacy in which an entity conforms to the institutionalized laws and regulations in a system (Scott, 1995). The platform also encourages hosts to post a photo and description of their interests and personality. We view the combination of all these personal elements as conducive to helping users gain familiarity with potential hosts. As such, rich profiles may lead to favorable cognitive legitimacy judgment by which hosts are assessed on the basis of comprehensibility (Aldrich & Fiol, 1994); that is, users can make sense of hosts' existence and purpose on the platform.

Ratings: Ratings are past users' evaluation of the rental based on six attributes: accuracy, communication, cleanliness, location, check-in, and value. Each criterion can be rated up to five stars to indicate the level of satisfaction. As attributes are defined by the platform, but are based on users' evaluation, ratings convey users' evaluation of the level of conformance of a host to the six attributes established by the platform. Thus, ratings may combine judgments of both legitimacy (conformance to the six attributes) and reputation (past performance), as they indicate past performance related to a host's conformance to rules, regulations, and social expectations. Specifically, users who evaluate the legitimacy of a host may look at the aggregated rating score to see if the host matches the quality standards of the platform. Alternatively, users who evaluate the reputation of a host may look at the specific scores along the attributes that matter to them and select hosts that outperform on these attributes. In conclusion, ratings consist of two information cues for users: aggregated scores indicate the level of conformance of a host to the quality standards of the platform while specific scores indicate the level of performance of a host on particular attributes.

Reviews: On Airbnb, users are particularly encouraged to leave a written comment of their experience during the stay. Reviews often take the form of descriptions of the behavior of the

host at the beginning and end of the stay, her or his helpfulness, the location, and other general features of the place. Thus, reviews are typically written to describe the specific rental in which the stay took place. Consequently, reviews serve as a basis for forming reputation judgment, as the evaluation is performed at the feature level. Prospective users who read reviews tend to evaluate the features of both the host and the place to predict their future experience with the stay and to compare the hosts on attributes that are important to them. Reviews systems on sharing platforms have often been described as “reputation systems” in the literature (Belk, 2014, p. 1598; Huang et al., 2014; Jones & Leonard, 2008). Nonetheless, as Airbnb also shows the number of reviews at the top of the review section, this figure may be used by prospective guests to evaluate the legitimacy of the host as a large number of reviews may be associated with an endorsement by past users. For example, a past study has shown that a large number of reviews on a restaurant tends to reassure prospective customers that many people had been in the restaurant before them (Zhang, Ye, Law, & Li, 2010). While the number of reviews alone says little or nothing about the specific quality of a host, a large number may indicate that a host has attracted many guests in the past, suggesting that this host belongs to the group of appropriate hosts.

In Table 1, we summarize how users may use information cues to form either legitimacy or reputation judgments.

**Table 1.** Evaluation goal and information cues on Airbnb

Evaluation goal	Form of judgment	Evaluative dimensions	Level of judgment	Potential relevant information cues on the platform
To select appropriate hosts based on their belonging to a group of appropriate hosts	Legitimacy	Host's conformance to the platform's expectations of rules, values (e.g., authenticity, transparency, safety, honesty), and general quality standards (accuracy, communication, cleanliness, location, check-in, and value)	Category—Does the host belong to a group of appropriate hosts endorsed by the platform	<p><u>Profile</u>: Number of IDs provided, membership history and description of personal interests</p> <p><u>Ratings</u>: <i>Aggregated score</i> on the six attributes (accuracy, communication, cleanliness, location, check-in, and value)</p> <p><u>Reviews</u>: Number of reviews</p>
To select hosts based on their past behavior, and how this behavior is indicative of future behavior. To identify hosts who are distinctively superior on attributes important to the user	Reputation	Individual and distinctive features of the host	Feature—Is the host predictable in terms of behavioral and performance attributes? How does the host compare with other hosts in the same category?	<p><u>Ratings</u>: <i>Specific score</i> on the six attributes (accuracy, communication, cleanliness, location, check-in, and value) that <i>both</i> matter to the user and distinguish the host from other hosts</p> <p><u>Reviews</u>: Detailed written reviews</p>

As social judgment literature adopts an audience perspective, the process of judgment formation systematically begins with an evaluation goal or what the evaluator is trying to achieve with the judgment. As a consequence, Table 1 shows that the goal of the evaluation determines the form of judgment users resort to. Users will then look at relevant information cues across the three information types to form the selected judgment. For example, if a user wants to select an appropriate host, she or he may evaluate the legitimacy of the host by

looking at membership history (date of account), the aggregated rating score of the six attributes, or the number of reviews. If a user desires a host that outperforms other hosts on specific attributes, she or he may evaluate the reputation of the host by reading the detailed reviews of past users. In this research, we focus on profile data (number of IDs, membership history, description of personal interests), ratings (aggregated scores of the six attributes), and written reviews as information cues that help users form judgments of legitimacy and reputation. We justify this approach in the methodology section.

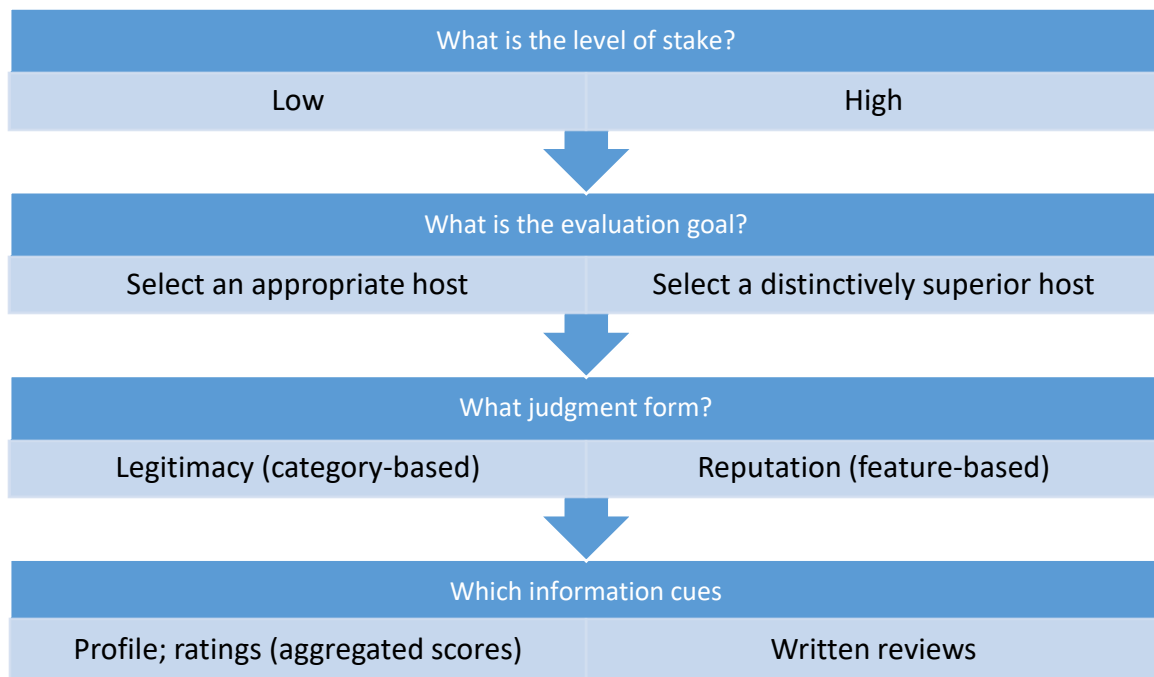
## **2.7 How Social Judgments Help Select Service Providers on Platforms**

Social judgment literature suggests the level of stake of a transaction plays a central role in determining the level of involvement in the evaluation task (Bitektine, 2011). Specifically, people use legitimacy judgment when both the stake of the transaction and the level of involvement in the decision are low (unwillingness to give time and cognitive effort to the evaluative task)—that is, when the task of selecting an exchange partner is routinized in simple scripted transactions. Typically, an individual only evaluates whether an exchange partner meets the minimum criteria on a set of attributes deemed appropriate for the transaction. Conversely, when both the stake of the transaction and the level of involvement in the decision are high, the individual will likely switch to reputation judgment to predict performance of the exchange partner. In short, the stake of a transaction determines the switch between the two forms of judgment.

In the context of Airbnb, social judgment literature would suggest that when considering a service provider for a relatively routinized or low-stake trip (e.g., traveling for work, spending a weekend in a nearby location), users will simply evaluate the familiar attributes of the host to determine whether he or she has provided the personal information required by the

platform and the extent to which the ratings are indicative of his or her conformance to the platform’s quality standards. Doing so enables users to render a legitimacy judgment that spares the host from scrutiny and expedites decision in this low-stake trip. However, if the economic and emotional stakes of the trip increase, users will likely switch to reputation judgment to evaluate the individual properties of both the host and the rental. On the platform, they can engage in such a judgment task by reading feedback from past users. Figure 1 summarizes how users rely on information cues to form their judgment of legitimacy or reputation according to the level of stake.

**Figure 1.** How users may evaluate hosts on Airbnb



In this research, our aim is to test the assumptions above through a qualitative study and two online experiments.

### 3. RESEARCH APPROACH



Following the evaluation process in Figure 1, the objective of this study is to explore (1) the information cues used to form a judgment (legitimacy or reputation) and (2) the role of stake in influencing the selection of judgment form. We employ a mixed-method approach to strike a balance between the exploratory phase and the confirmatory phase (Venkatesh, Brown, & Bala, 2013; Venkatesh, Brown, & Sullivan, 2016). The first phase used a combination of qualitative and quantitative methods to explore how users form both judgment of legitimacy and of reputation in their evaluation of hosts and what information cues they use for each judgment form.

The second phase consisted of two online experiments to examine the role of stake in influencing users' selection of a judgment form. The unit of analysis here is individual members on sharing platforms (i.e., hosts and guests on Airbnb). Although legitimacy and reputation have often referred to organizations in the organizational literature, these concepts have also been applied to individuals such as leaders (Mehra, Dixon, Brass, & Robertson, 2006; Tost, 2011). Therefore, the concepts of legitimacy and reputation judgments have been shown to apply to both organizations and persons.

#### **4. QUALITATIVE STUDY**

We undertook this study in two stages. While the first stage aimed to investigate how users of Airbnb use available information (profile, ratings, and reviews) to evaluate a rental opportunity, the second stage aimed to check the accurateness of our earlier findings.

##### **4.1 Stage 1**

In the first stage, we interviewed a convenience sample of 40 users of Airbnb on their use of the three types of information (profile, ratings, and reviews) as cues to evaluate a rental opportunity. The 40 users were between 18 and 58 years of age (average: 41 years), 50% were

women, all had moderate experience on the platform (approximately three reservations/year on average), and were recruited as volunteers in a large business school. Following the rule of informational redundancy (Lincoln & Guba, 1985), we ceased to recruit participants when no new information emerged from new interviews.

### *Information cues*

We first asked participants to indicate the information they look at when evaluating a rental opportunity. A broad consensus (32) indicated by order of importance “written reviews,” “ratings,” “number of reviews,” and “profile data” with a focus on “number of IDs” and “membership date.” A near unanimous agreement (37) was reached about written reviews as an essential information for booking the stay, that is, users would always read reviews to some extent independently of the purpose of stay.

### *Role of stake*

We further investigated the reasons why participants read reviews for all purposes of stay by asking them to elaborate on this practice. When asked why they read reviews even for routine, low-stake trips, the participants noted that the easily accessible reviews tend to be more reliable than profile information. Regarding when they use hosts’ profile as a primary source of information, they indicated that they would consider only information validated by Airbnb, such as membership date, personal data, or the hosts’ photo if they were new to the platform and thus had no reviews available. Nearly, all participants also agreed that they would look at the number of reviews and then scroll through a few reviews on the first page of results if the trip stakes were low but would read more reviews spanning several pages if the stakes were high. In the latter case, they would systematically complement the reviews with hosts’ profile information.

## **4.2 Stage 2**

In the second stage, we used a mouse-tracking software to track the scrolling and mouse movements of an additional convenience sample of 40 users to check the accurateness of our earlier findings. The 40 users were recruited on a voluntary basis from a large business school and matched the demographics of the sample in the first phase (age between 18 and 55, average age of 40, and moderate experience on Airbnb). Mouse-tracking techniques are useful in our study as they allow us to observe users in action, without them being aware of this, and to cross-check our earlier findings. We asked the users to evaluate a fictitious Airbnb website that we replicated using existing real rentals and host profiles. We manipulated the level of stake by location (close to vs. away from home) and time-length of stay (short vs. long) because decision-making is assumed to be characterized by lower involvement when trips are of shorter duration and closer to home (Ene & Schofield, 2011). Half the participants evaluated a low-stake trip to Manchester (one night), and the other half evaluated a high-stake trip to a foreign country, Mexico City (seven nights). Appendices 1 and 2 show the mouse movements of users (we hid the photos to ensure anonymity), represented by the luminescent spots on the photo, in both groups. The results show that users focused on reviews in both groups. However, while the mouse movements were similar on the first pages of reviews, they differed on the third page of reviews. That is, users in the high-stake trip were more active than users in the low-stake trip from the third page of reviews (those who went beyond the third page were 85% in the high-stake group and 30% in the low-stake group), indicating that the former group had a more sustained interest in reading reviews than the latter group. This finding confirmed participants' statement in the interviews that they would read fewer reviews for low-stake trips but tend to read more for high-stake trips.

#### **4.3 Conclusion from Exploratory Qualitative Studies**

While profile data and ratings are deemed useful to some extent, users tend to read reviews for all trips regardless of the level of stakes involved. This finding may counter the

assumptions of social judgment literature (Bitektine, 2011). However, we offer that the easy access to all information induces users to systematically select the most reliable form of judgment, namely reputation. As all information is made available to users independently of the purpose and length of their stay, and written reviews tend to be the more reliable source of information, users are naturally inclined to rely on this cue to evaluate a rental opportunity.

Of the information cues represented in our literature review (Table 1), we build on the findings of the qualitative study to examine profile data (membership date and number of IDs), aggregated ratings score, and written reviews in our online experiments. We omitted cues that could not be manipulated in a sufficiently objective way in experimental procedures. Therefore, we did not examine other profile data, such as photo of the host and description of personal interests as these tend to be evaluated subjectively. Furthermore, specific ratings scores were not included as the focus on specific scores is highly person-dependent. Finally, number of reviews was discarded because unlike other online platforms, Airbnb does not indicate the valence of reviews. For instance, eBay shows the distribution of feedback as being positive, neutral or negative. Amazon provides the score that a buyer attributes to the seller or product above the written review to indicate the level of satisfaction. While we agree that a certain threshold of reviews may legitimate a host, we were also uncertain about the potential impact of negative reviews on the overall legitimating power of number of reviews. The marketing literature provides ample evidence that negative word-of-mouth has a much greater impact than positive word-of-mouth (Richins, 1983). The cues we examine in our experiments could be reasonably manipulated and understood by users in online experiments: Profile data (membership date indicates the “age” of the account; number of IDs indicates the number of identification documents a user has provided to Airbnb); aggregated ratings score indicates the average score of the host for a particular rental on the six attributes; and written reviews indicates whether the host has received feedback from users.

## **5. PRELIMINARY QUANTITATIVE STUDY: INFORMATION CUES AND REPUTATION VERSUS LEGITIMACY JUDGMENTS**

Our qualitative study provides some indications that users tend to approach profile and ratings score information of hosts on Airbnb differently under high- versus low-stake conditions. To gain further understanding into the roles of the information cues, we conducted a factor analysis (FA) to assess whether the information cues retained for further analysis (i.e., profile data, aggregated ratings score, and written reviews) generate distinct forms of judgment, namely, legitimacy and reputation in the context of Airbnb.

In stage 1, we used the literature on reputation and legitimacy to derive six items to capture legitimacy and reputation. In stage 2, we used a sample of 30 users who had taken part into the qualitative study (stage 1) to refine these items. Legitimacy items were adapted from Alexiou and Wiggins (2019) and Elsbach (1994), and consisted of two underlying dimensions, namely, cognitive legitimacy captured with “how useful is the information below in assessing whether the host has the right to offer rentals on Airbnb” and “how useful is the information below in assessing whether the host’s presence on the platform is appropriate”; and normative legitimacy assessed with “how useful is the information below in assessing whether the host meets the standards of quality as expected by the community” and “how useful is the information below in assessing whether the host will provide a satisfactory guest experience.” As reputation is rarely measured directly (Rindova et al., 2005), we built on the seminal work of Bitektine (2011), Deephouse and Carter (2005), and Lange et al. (2011) to develop a direct measure of reputation items with “how useful is the information below in predicting the future behavior of the host” and “how useful is the information below in differentiating the host from other hosts.” In stage 3, we conducted an FA in STATA with the total sample of 205 Airbnb users to verify that the six items loaded on three factors corresponding to legitimacy

(cognitive and normative) and reputation. Table 2 shows the descriptive statistics and the results of the FA.

**Table 2.** Descriptive statistics of factor analysis and factor loadings

Variable	Obs.	Mean	Std. Dev.	Min	Max	Factor 1	Factor 2	Factor 3
<b>cog1</b>	205	4.107	1.673	1	7			0.872
<b>cog2</b>	205	4.263	1.641	1	7			0.831
<b>nor1</b>	205	4.126	1.837	1	7		0.849	
<b>nor2</b>	205	4.121	1.773	1	7		0.890	
<b>rep1</b>	205	4.463	1.637	1	7	0.872		
<b>rep2</b>	205	4.302	1.667	1	7	0.879		

As seen in Table 2, the principal component FA retained three factors with Eigen-values above 1. After varimax rotation, the factor loadings (all above 0.80) show that the items loaded as predicted on the respective factor, that is, cog1 and cog2 (cognitive legitimacy,  $\alpha=0.73$ ), nor1 and nor2 (normative legitimacy,  $\alpha=0.73$ ), and rep1 and rep2 (reputation,  $\alpha=0.70$ ). In conclusion, the results indicate that the two forms of judgment are related to the three types of information cues under study.

Finally, to show that the items were associated, respectively, with legitimacy (cognitive and normative) and reputation judgments, we asked three groups of respondents (N=205) to indicate on a 7-point Likert-type scale (1—not at all useful to 7—very useful), the degree of usefulness of a specific information type (profile, aggregated ratings score, or reviews) for a particular purpose: Group 1 (n=69) evaluated the usefulness of the profile of a host on the six items, group 2 (n=68) evaluated the usefulness of the aggregated ratings score on the six items, and group 3 (n=68) evaluated the usefulness of reviews on the six items. The results of a Multivariate Analysis of Variance (MANOVA) showed a significant difference between the means of perceived usefulness across the three groups (Wilks' lambda :  $F=5.76, p<.001$ ): Group 1, which evaluated the usefulness of profile reported higher means for cognitive

legitimacy items (*cognitive legitimacy*=5.25; *normative legitimacy*=3.00; *reputation*=3.15); group 2, which evaluated the usefulness of aggregated ratings score reported higher means for *normative legitimacy* (*cognitive legitimacy*=3.26; *normative legitimacy*=5.22; *reputation*=4.55); group 3, which evaluated the usefulness of reviews reported higher means for reputation items (*cognitive legitimacy*=4.02; *normative legitimacy*=4.16; *reputation*=5.46).

The results above, which show that the different information cues are associated, respectively, with the legitimacy and reputation judgments, serve as the basis for us to further investigate how users may assess the two types of judgment-related information cues under high- versus low-stake condition, as described in the experiment below.

## 6. EXPERIMENT 1

Our qualitative study revealed that users read reviews independently of the level of stake because these were accessible on the same webpage of the rental opportunity, thus forming a judgment of reputation for any purpose of trip. The aim of the first experiment is to further investigate this result. Specifically, if users read reviews for any purpose of stay, are other information cues useful in the host evaluation process? Even though users may read reviews in both low- and high-stake trips, we suggest that the level of stake still determines the information cues that users access first. Although users read reviews for low-stake trips, the principle of cognitive economy (Rescher, 1989) suggests that their first evaluative task will be to routinely categorize the host in a familiar group to save cognitive effort. In other words, while users may eventually read the reviews on the webpage of a rental opportunity, the level of stake influences the sequence of judgment formation such that low-stake trips will prompt users to form a legitimacy judgment *first* and high-stake trips will prompt users to form

reputation judgment *first*. Therefore, we argue that even if users read reviews in both low- and high-stake trips (hypothesis 1), users will access legitimacy-related cues first in low-stake trips and reputation-related cues first in high-stake trips (hypothesis 2):

**H1:** *The level of stake (low and high) has no influence on the importance of reviews to users.*

**H2:** *The level of stake (low and high) has an influence on the information cues users access first such that users will access legitimacy-related cues first in low-stake trips and reputation-related cues first in high-stake trips*

## **6.1 Participants and Procedure**

We collected data using the services of a consumer panel company which randomly assigned 202 participants in the United Kingdom (randomly selected in a database of 60 thousand consumers) to a two-condition online experiment (low- vs. high-stake trip). The sample of users was obtained from a market study firm in the UK which has access to a panel of 60,000 consumers in the country. We asked the firm to send the online questionnaire to a sample of 202 participants who had an Airbnb account at the time of the study. A sample size of 202 is considered to be very appropriate for running multiple regressions involving six predictors (Knofczynski & Mundfrom, 2008) and well-above common recommendations for conducting means comparison tests (VanVoorhis & Morgan, 2007). We manipulated the level of stake by location and time-length of stay, as we had done in the qualitative study. The low-stake trip involved evaluating a rental on a fictitious Airbnb website for a one-night trip in Manchester, while the high-stake trip was a 1-week rental in Mexico City. We replicated the Airbnb website using information and reviews from two existing hosts (one in the United Kingdom and one in Mexico City). Given that we manipulated the level of stakes by varying trip location and duration, we attempted to keep other things equal by showing the same photo



and name for the host, the same number of reviews, and a similar level of ratings.

Nonetheless, we did not modify the written reviews, as these must be consistent with the location. Moreover, to check the internal validity of our experiment, we ensured that varying location and duration was sufficient to manipulate the level of stakes.

## **6.2 Pre-test and manipulation check**

We conducted a pre-test to validate the stimuli to be used in the main experiment and used a sample of 30 users who had taken part into the qualitative study to ensure that users perceived the Manchester trip condition as low stake and the Mexico City trip condition as high stake. Recent recommendations in experimental methods suggest that validating the stimulus of an experiment in a pre-test before the main data collection is more appropriate than performing manipulation checks after the main data collection (Grégoire, Binder, & Rauch, 2019). In both conditions, we asked the participants to rate the importance of the trip to them “how important is this trip to you?” The result of the manipulation check indicated that the users viewed the two levels of manipulation as sufficiently efficient to create the low- and high-stake conditions (2.37 vs. 5.95,  $p < .01$ ).

## **6.3 Measures**

We measured participants’ evaluation of the importance of each type of information cue (profile data, aggregated ratings score, and reviews) on a 7-point Likert-type scale by asking “how important is this information to you in evaluating this rental?” We also asked participants to indicate the type of information they accessed first in their evaluation “what was the first information you looked at in evaluating this rental?” by choosing one of the three options: (1) profile, (2) ratings, and (3) reviews. Although the three types of information cues tend to be categorical in nature, they may be ordinal in terms of the cognitive effort required to process them. Profiles are evaluated on the basis of how much the host was willing to

conform to the platform's request for personal data. Aggregated ratings score requires slightly more cognitive effort as users need to process the scores on the six attributes and assess whether the minimal performance level is met. Reviews require even more cognitive effort, as users need to spend time and effort on reading them to form a judgment. We also measured the extent to which participants would have liked to read more detailed reviews on the pages of reviews (1 = not at all, 7 = definitely). Finally, we controlled for a series of demographic variable that may influence the evaluation, including age (four groups: 1=18–25; 2=26–35; 3=36–45; 4=46–55), income (four groups: 1=10k–20k; 2=20k+1–40k; 3=40k+1–60k; 4=> 60k), gender (two groups: 1=male and 2=female), travel frequency per year (four groups: 1=0–2; 2=3–4; 3=4–6; 4=> 6), and use frequency on Airbnb is based on use frequency per year (four groups: 1=0–2; 2=3–4; 3=4–6; 4=> 6).

#### **6.4 Results and Findings**

Table 3 shows the descriptive statistics and correlations between the variables. The sample statistics indicate that the age criterion leans toward groups 3 and 4 ( $M=2.91$ ,  $SD=1.14$ ), income leans toward the first and second group ( $M=2.13$ ,  $SD=0.87$ ), gender ( $M=1.45$ ,  $SD=0.49$ ), travel experience ( $M=2.27$ ,  $SD=0.86$ ), and use frequency on Airbnb ( $M=2.65$ ,  $SD=1.05$ ) appear to be relatively evenly distributed. To examine the impact of level of stakes on the perceived importance of the three types of information cues, we performed a series of *t*-tests to compare the means between the low- and high-stake groups. As Table 4 shows, the difference in means between the two groups was not significant for ratings and reviews (ratings: 6.06 vs. 6.17,  $p > .05$ ; reviews: 6.19 vs. 6.15,  $p > .05$ ), but slightly significant for profile (5.76 vs. 5.48,  $p=.04$ ). Given that, we hypothesize the absence of relationship between level of stake and importance of reviews, we conducted additional analyses by examining confidence intervals around the effect size to assess the result's "true or false equivalence" (Nakagawa & Cuthill, 2007). Indeed, a non-significant result may be due to poor data

collection or lack of statistical power. This analysis is also useful for confirming significance as the p-value of profile indicates near non-significance. Table 4 shows that all the 95% confidence intervals for profile, ratings, and reviews included zero, which suggests no difference in means between the two groups (Nakagawa & Cuthill, 2007). The result indicates that the level of stakes had no effect on the perceived importance of the information cues, including reviews, thus supporting H1. To test H2 that the level of stakes will determine the type of information cues that users access first, our results confirm that users in the low-stake condition were more inclined to access legitimating information cues while users in the high-stake condition were more inclined to access reputational information cues (1.78 vs. 2.44,  $p < .01$ ). Indeed, a lower mean implies that users more frequently chose option 1 (profile), while a higher mean implies more choice of option 3. As previously stated, though categorical, the three types of information cues may also be ordinal depending on the level of cognitive effort required to process them. A simple frequency statistic indicates that users chose profile and ratings more as the first information cues in the low-stake group (profile: 37%; ratings: 47%; reviews: 15%), while reviews were the dominant information type in the high-stake group (profile: 6%; ratings: 44%; reviews: 50%). Therefore, we confirm H2. Finally, our results also reveal that users in the high-stake condition were inclined to want to read more reviews than those in the low-stake condition (5.42 vs. 4.64,  $p < .01$ ). This result suggests that though users in both conditions equally perceived reviews as important, those in the high-stake condition expressed a higher need to access more reviews to form their judgment. Our results from the mean comparisons were confirmed in the multiple regression analyses when we controlled for the demographic variables, travel frequency, and use frequency on Airbnb (see Table 5). The effect of level of stakes on types of information first accessed ( $\beta = 0.59$ ,  $p < .01$ ) and need for more reviews ( $\beta = 0.71$ ,  $p < .05$ ) was significant, but it was not significant for the importance of ratings ( $\beta = 0.12$ ,  $p > .05$ ) and reviews ( $\beta = -0.04$ ,  $p > .05$ ). Although the regression

suggests a significant effect of level of stake on importance of profile ( $\beta = -0.40, p = .04$ ), our earlier analysis of confidence interval reveals that this significant result is not robust.

We ran a statistical power analysis for two independent means using the “power two means” function in Stata (version 13). Given that we did not find a significant difference for “importance of profile,” “importance of ratings score,” and “importance of reviews,” we set a target means-difference of 0.50 for the power analysis. The statistical power was 80% for “importance of profile,” 98% for “importance of ratings score,” 97% for “importance of reviews,” and 100% for “first information cue accessed” (two-tailed and  $p = .05$  for error probabilities for all analyses). We conclude that the sample sizes were appropriate.

**Table 3.** Descriptive Statistics and Correlations of Experiment 1

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10	11
1. Age	2.91	1.14	1										
2. Income	2.13	0.87	-0.05	1									
3. Gender	1.45	0.49	0.15*	-0.19**	1								
4. Travel	2.27	0.86	0.26**	0.17*	0.19**	1							
5. Use frequency	2.65	1.05	-0.09	0.24**	-0.11	0.43**	1						
6. Profile	5.61	1.17	-0.05	-0.20**	0.02	-0.05	-0.24**	1					
7. Ratings	6.12	0.87	-0.22**	0.05	-0.12	-0.00	0.06	0.36**	1				
8. Reviews	6.17	0.92	-0.19**	-0.02	-0.06	-0.13*	0.00	0.14*	0.54**	1			
9. Info. type	2.12	0.72	-0.01	0.09	0.07	0.19**	-0.09	-0.08	0.31**	0.08	1		
10. Info. need	5.04	1.29	-0.21**	-0.04	-0.07	-0.04	-0.14*	0.12	0.21**	0.24**	0.21**	1	
11. Stake	1.51	0.50	-0.07	0.02	0.14*	0.04	-0.13	-0.12	0.07	-0.02	0.45**	0.30**	1

\* $p < .05$ .

\*\* $p < .01$ .

**Table 4.** Summary Statistics for Experiment 1

Variables	Low stake	High stake	t-value for equality of means and associated p-value (two-tailed)	[95% Conf. Interval]
<b>Importance of profile</b>	Mean=5.76 (SD=1.25, $n=98$ )	Mean=5.48 (SD=1.25, $n=104$ )	1.721 (0.043)	-0.041 0.610
<b>Importance of ratings score</b>	Mean=6.06 (SD=0.91, $n=98$ )	Mean=6.17 (SD=0.82, $n=104$ )	-1.068 (0.856)	-0.372 0.110
<b>Importance of reviews</b>	Mean=6.19 (SD=0.90, $n=98$ )	Mean=6.15 (SD=0.95, $n=104$ )	0.305 (0.380)	-0.218 0.298
<b>First information</b>	Mean=1.78	Mean=2.44	-7.190	-0.836 -0.476

<b>cue accessed</b>	(SD=0.69, n=98)	(SD=0.60, n=104)	(0.000)	
<b>Need for more reviews (Info. need)</b>	Mean=4.64 (SD=1.27, n=98)	Mean=5.42 (SD=1.20, n=104)	-4.481 (0.000)	-1.123 -0.436

**Table 5.** Multiple Regressions of Experiment 1

Variables	Model 1 DV= Profile	Model 2 DV= Profile	Model 3 DV= Ratings score	Model 4 DV= Ratings score	Model 5 DV= Reviews	Model 6 DV= Reviews	Model 7 DV= Info. Type	Model 8 DV= Info. Type	Model 9 DV= Info. Need	Model 10 DV = Info. Need
<b>Controls</b>										
<b>Age</b>	-0.12 (0.07)	-0.14* (0.07)	-0.18** (0.05)	-0.17** (0.05)	-0.13* (0.06)	-0.13* (0.06)	-0.08 (0.04)	-0.04 (0.04)	-0.30** (0.08)	-0.26* (0.08)
<b>Income</b>	-0.24* (0.09)	-0.23* (0.09)	0.00 (0.07)	0.00 (0.07)	-0.03 (0.07)	-0.03 (0.07)	0.07 (0.05)	0.05 (0.05)	-0.06 (0.10)	-0.09 (0.10)
<b>Gender</b>	-0.13 (0.17)	-0.08 (0.17)	-0.18 (0.12)	-0.19 (0.13)	-0.03 (0.13)	-0.02 (0.14)	0.02 (0.10)	-0.05 (0.09)	-0.26 (0.18)	-0.36 (0.18)
<b>Travel</b>	0.19 (0.11)	0.22* (0.11)	0.09 (0.08)	0.08 (0.08)	-0.11 (0.09)	-0.10 (0.09)	0.28** (0.06)	0.23** (0.06)	0.23 (0.12)	0.17 (0.12)
<b>Use frequency</b>	-0.31** (0.08)	-0.31** (0.13)	-0.01 (0.06)	-0.00 (0.06)	0.03 (0.07)	0.02 (0.07)	-0.19** (0.05)	-0.13** (0.05)	-0.28* (0.09)	-0.21* (0.09)
<b>Independent variable</b>										
<b>Stake</b>		-0.40* (0.16)		0.12 (0.12)		-0.04 (0.13)		0.59** (0.09)		0.71** (0.17)
<b>Constant</b>	7.08**	7.69**	6.71**	6.52**	6.84**	6.90**	2.02**	1.11**	6.69**	5.61**
<b>Adjusted R<sup>2</sup></b>	0.08	0.10	0.04	0.04	0.02	0.01	0.08	0.24	0.07	0.14
<b>F-value</b>	4.62**	4.97**	2.85*	2.54*	1.96	1.64	4.72**	11.90**	4.12**	6.55**
<b>Obs.</b>	202	202	202	202	202	202	202	202	202	202

\* $p < .05$ .

\*\* $p < .01$ .

Standard errors are in parentheses.

## 6.5 Additional study

Given that we left the original photo and written reviews of the rental in Manchester and Mexico City to be consistent with the location, as a robustness check, we replicated Experiment 1 using the same rental asset, keeping all things equal to eliminate the potential confounds due to the photo and reviews. We manipulated the purpose of stay: 2-day professional purpose in the low-stake condition versus 2-week family purpose in the high-stake condition. These two conditions were suggested by some participants in the qualitative study. A pre-test (n=35) shows that the purpose of stay (2 days for professional purpose vs. 2 weeks for family purpose) was a valid stimulus as participants perceived the stake to be

significantly lower for the professional versus family purpose (2.45 vs. 5.39,  $p < .01$ ). The main data collection ( $n=125$ ) yielded results similar to those of Experiment 1: We did not find a significant difference in the perceived importance of reviews between the two conditions (6.01 vs. 5.87,  $p > .05$ , confidence interval includes a “0”). Therefore, reviews are perceived to be important regardless of the level of stake. Regarding which information cues users access first, we also found similar results: users tend to access profile and aggregated ratings cues first in low-stake condition and written reviews in high-stake condition (1.81 vs. 2.50,  $p < .01$ ). The results confirm those of Experiment 1, providing further support for our view that the level of stake has no influence on the importance of reviews to users (H1), but has an influence on the information cues users access first such that users access legitimacy-related cues first when the level of stake is low and reputation-related cues first when the level of stake is high (H2).

## **6.6 Conclusion of Experiment 1**

We conclude that while low-stake trips prompt users to first form a legitimacy judgment by accessing profile data and aggregated ratings score, users still rely on reputation judgment by reading reviews in their evaluation task. A possible explanation is that users in both groups relied on reputation judgment because reviews were readily available to them, thus requiring little search effort on their part to search for this type of information cues. As reputation judgments tend to be more reliable than legitimacy judgments in the selection of hosts, users are induced by the availability of reviews to form reputation judgments regardless of the level of stake. Indeed, the availability of feature-based information on the platform greatly lowers search efforts on the part of users and therefore prompts them to use the most reliable form of judgment. However, this finding raises the question of whether users really need reviews to build confidence in a host for low-stake trips as these are typically low-risk transactions for

them. Consequently, we conduct a second experiment to examine the role of reviews in influencing users' decision outcomes in low-stake trips in order to find out whether reviews are useful in this type of trips.

## **7. EXPERIMENT 2**

As low-stake trips involve low risk for users, the relevance of showing extensive, but potentially unnecessary information to prospective users might be questioned. The findings of Experiment 1 prompted us to test the contention that users in low-stake trips are able to make efficient host selection decision by relying only on legitimacy judgment rather than on both forms of judgment. Specifically, we refer back to Bitektine's (2011) initial assumption that resorting to legitimacy judgment is optimal for low-stake routine tasks. In other words, while platforms are naturally inclined to provide as much information as possible to help users make decisions, we argue that the level of information is not always optimal and should be adapted to the motivations of users.

In the case of Airbnb, we contend that the decision-making process of users in low-stake trips is optimal when they use legitimacy rather than reputation judgment, or both. Therefore, we hypothesize that increasing the level of information (by providing all three types of information cues) does not improve users' confidence in the host or the stay:

**H3:** *In a low-stake trip, the effect of reviews on a user's level of confidence in a (a) host and (b) stay is diminished*

### **7.1 Participants and Procedure**

Data were collected using the services of a consumer panel company which randomly assigned 205 UK participants (out of 60 thousand consumers) to a two-condition experiment (low vs. high information) for a low-stake trip. We followed the same rule of thumb for

sample size as in Experiment 1. Participants in the low-information condition were presented with the ratings of the rental based on 18 reviews, but without the possibility to read the associated 18 reviews (absence of reviews), while in the high-information condition, participants were presented with both the ratings based on 18 reviews and the actual 18 reviews (presence of reviews). The cutoff number of 18 reviews was the median number of reviews computed from a random sample of 300 rentals in the Liverpool area at the time of the study. We deemed this number to be appropriate as a low number may frustrate users who need more reviews to form a reputation judgment, but a high number may reinforce the ratings score alone. In both cases, a bias may result from extremes. The 18 reviews were extracted from an existing rental and were ensured to be consistent with the ratings shown to our sample participants. As Zervas et al. (2015) found that 95% of all Airbnb rentals tend to be rated above average with aggregated ratings scores between 4.5 and 5 stars, the reviews in our experiment were mostly positive. We also ensured that the reviews did not contain any contradictions or details that would trigger a mental alert from users (Tost, 2011), as these would affect the evaluations of the participants. A sample page of the reviews is shown in Appendix 3. In both conditions, the low-stake trip was a one-night stay in Liverpool. Both conditions showed a similar photo of the host and the rental along with basic membership information, as this is expected on Airbnb. Given that our stimulus is objective in nature (presence or not of an information type), we did not perform manipulation check.

## **7.2 Measures**

We asked the participants to indicate their confidence in the host and the stay and their intention to book the rental in evaluating a one-night stay in Liverpool. All items used a 7-point Likert-type scale. As in the first experiment, we controlled for a series of demographic variables that may affect participants' evaluation processes, including age, income, gender, travel frequency, and use frequency on Airbnb.



### 7.3 Results and findings

Table 6 shows the descriptive and correlation statistics of the variables. The sample statistics were relatively similar to those found in Experiment 1: Age ( $M=2.63$ ,  $SD=1.06$ ), income ( $M=2.37$ ,  $SD=1.06$ ), gender ( $M=1.49$ ,  $SD=0.50$ ), travel experience ( $M=2.24$ ,  $SD=0.78$ ), and use frequency on Airbnb ( $M=2.25$ ,  $SD=1.02$ ). As Table 7 indicates, there was no statistical difference between the two conditions in “confidence in the host” (5.13 vs. 5.31,  $p > .05$ ) and “confidence in the stay” (5.40 vs. 5.36,  $p > .05$ ), which means that for low-stake trips, a lower level of information did not lower the level of confidence in both the host and the stay. We analyzed the 95% confidence intervals to confirm the absence of any difference in the means between the two groups, as both tests include a zero in the intervals (Nakagawa & Cuthill, 2007). Users showed similar confidence levels in the rental when presented with the ratings only or with both the ratings and the associated reviews. This confirms H3a and H3b that the presence of reviews is unnecessary for users evaluating a low-stake trip. Surprisingly, participants in the low-information condition also exhibited a higher intention to book (5.36 vs. 4.57,  $p < .01$ ) than those in the high-information condition. This result indicates an increased impact of showing less (or optimal) information to users evaluating low-stake trips. In Table 8, our multiple regression analyses show that the results still hold when we control for demographic and behavioral variables. “Level of information” had no significant effect on “confidence in the host” ( $\beta = 0.16$ ,  $p > .05$ ) and “confidence in the stay” ( $\beta = -0.07$ ,  $p > .05$ ), but its effect on “intention to book” ( $\beta = -0.91$ ,  $p < .01$ ) was significant. When the level of information increases (by including reviews), users’ “intention to book” decreases.

We ran a statistical power analysis for two independent means using the “power two means” function in Stata. Given that the results for “confidence in the host” and “confidence in the stay” were non-significant, we calculated the statistical power for a difference in means of 0.50 for these two variables, which was deemed reasonable as the difference we found for

“intention to book” was 0.79. The statistical power was 97% for “confidence in the host,” 85% for “confidence in the stay,” and 96% for “intention to book” (two-sided test and  $p=.05$  for error probabilities for all analyses). We conclude that the sample sizes were appropriate.

**Table 6.** Descriptive Statistics and Correlations of Experiment 2

Variables	Mean	SD	1	2	3	4	5	6	7	8	9
1. Age	2.63	1.06	1								
2. Income	2.37	1.06	–0.19**	1							
3. Gender	1.49	0.50	0.06	0.00	1						
4. Travel	2.24	0.78	0.12	0.27**	0.05	1					
5. Use frequency	2.25	1.02	–0.23**	0.45**	–0.26**	0.31**	1				
6. Confid. host	5.22	0.93	0.34**	0.11	–0.09	0.05	0.06	1			
7. Confid. stay	5.38	1.19	0.32**	0.24**	0.05	0.15*	0.03	0.76**	1		
8. Intention	4.95	1.56	0.06	0.24**	–0.00	–0.03	0.09	0.59**	0.61**	1	
9. Information	5.13	1.67	0.18**	–0.04	0.06	–0.25**	–0.12	0.66**	–0.63**	–0.54**	1

\* $p < .05$ .

\*\* $p < .01$ .

**Table 7.** Summary Statistics for Experiment 2

Variables	Low information	High information	<i>t</i> -value for equality of means and associated <i>p</i> -value (two-tailed)	[95% Conf. Interval]
<b>Confidence in host</b>	Mean=5.13 (SD=0.84, $n=100$ )	Mean=5.31 (SD=1.00, $n=105$ )	–1.416 (0.920)	–0.440 0.072
<b>Confidence in stay</b>	Mean=5.40 (SD=1.03, $n=100$ )	Mean=5.36 (SD=1.33, $n=105$ )	0.228 (0.409)	–0.291 0.367
<b>Intention to book</b>	Mean=5.36 (SD=1.42, $n=100$ )	Mean=4.57 (SD=1.61, $n=105$ )	3.706 (0.000)	0.369 1.208

**Table 8.** Multiple Regressions of Experiment 2

Variables	Model 1 DV= Confidence Host	Model 2 DV= Confidence Host	Model 3 DV= Confidence Stay	Model 4 DV= Confidence Stay	Model 5 DV= Intention To book	Model 6 DV= Intention To book
<b>Controls</b>						
<b>Age</b>	0.35** (0.06)	0.34** (0.06)	0.42** (0.07)	0.42** (0.07)	0.22* (0.10)	0.28** (0.10)
<b>Income</b>	0.15* (0.06)	0.15* (0.06)	0.35** (0.08)	0.35** (0.08)	0.42** (0.11)	0.39** (0.11)
<b>Gender</b>	–0.18 (0.12)	–0.21 (0.12)	0.06 (0.15)	0.08 (0.16)	0.01 (0.22)	0.21 (0.21)
<b>Travel</b>	–0.07 (0.08)	–0.05 (0.08)	0.03 (0.10)	0.01 (0.10)	–0.29 (0.14)	–0.43** (0.14)
<b>Use frequency</b>	0.06 (0.07)	0.05 (0.07)	–0.01 (0.09)	–0.01 (0.09)	0.07 (0.12)	0.14 (0.12)

<i>Independent variable</i>						
<b>Level of information</b>		0.16 (0.12)		-0.07 (0.15)		-0.91** (0.21)
<b>Constant</b>	4.20**	3.99**	3.28**	3.38**	3.81**	4.96**
<b>Adjusted R<sup>2</sup></b>	0.15	0.15	0.18	0.18	0.06	0.14
<b>F-value</b>	8.20**	7.15**	10.17**	8.48*	3.98**	6.69**
<b>Obs.</b>	205	205	205	205	205	205

\* $p < .05$ .

\*\* $p < .01$ .

Standard errors are in parentheses.

## 7.4 Additional study

The stimulus in the experiment was absence (no access to reviews) versus presence of reviews (access to reviews on the same webpage). We thought that not granting access to reviews in the “absence of reviews” condition would facilitate the interpretation of results. However, not allowing access to reviews would be unrealistic, as platforms, such as Airbnb, do not completely obstruct users from accessing review. Therefore, as a robustness check, we conducted an additional study ( $n=113$ ) using the same settings and procedures, but manipulated “difficulty of access to reviews” by granting users the possibility to access the reviews if they want to read them (condition 1) versus showing the reviews directly on the same webpage (condition 2). No manipulation was needed as the stimulus was objective in nature: users were able to read the reviews by clicking on the “read reviews” button versus read the reviews on the same webpage. The results of the additional study were similar to those of Experiment 2: Users have similar confidence in the host (5.29 vs. 5.18,  $p > .05$ , confidence interval includes a “0”) and the stay (5.46 vs. 5.16,  $p > .05$ , confidence interval includes a “0”) in both experimental conditions. Moreover, users’ intention to book is higher in the high-difficulty group than in the low-difficulty group (5.43 vs. 4.43,  $p < .01$ , confidence interval does not include a “0”). The results of the additional study confirmed the findings from Experiment 2, providing further support for our view that showing reviews diminishes users’ intention to book when the level of stake is low.

## 7.5. Conclusion of Experiment 2

While our qualitative study and first experiment showed that users read and value reviews regardless of the level of stake, in Experiment 2, we examined the impact of reviews on selection decision for low-stake trips. Low-stake contexts are relevant in this study as e-commerce research has demonstrated that increasing the amount of information provided to consumers may cause information overload, adding complexity and making choice difficult because of limited information-processing capacity (Baek, Ahn, & Choi, 2012; Gao, Zhang, Wang, & Ba, 2012; Singh et al., 2017). As consumers tend to limit the intake of information in order to save cognitive energy when considering a particular product (Malhotra, 1984), providing more information beyond what consumers are willing or able to process cognitively can lead to more confusion, less confidence, and less satisfaction (Lee & Lee, 2004), and inhibits consumers' ability to set priorities and to recall prior information (Hu & Krishen, 2019; Lurie, 2004). In a study on social networks, information overload was found to be associated with fatigue and dissatisfaction of users (Zhang, Zhao, Lu, & Yang, 2016), which can lead consumers to make poorer choices or to make no choices at all (Ghose, Ipeirotsis, & Li, 2014; Kuksov & Villas-Boas, 2010).

To help consumers make better purchasing decisions, e-commerce websites should present online ratings in a mean rather than distribution format to increase processing fluency (Kostyk, Niculescu, & Leonhardt, 2017), make online reviews more valuable by promoting helpfulness votes by potential buyers (Singh et al., 2017), and adapt the degree of information control to the degree of consumers' expertise and motivation (Baek et al., 2012; Wu & Lin, 2006, 2012). Social judgment literature also suggests legitimacy judgment as an optimal form of evaluation for low-stake, routinized transactions. The results lend support to our contention that showing extensive information that is not adapted to the level of motivation does not improve users' confidence in a transaction and can even backfire by decreasing their decision-

making. Table 9 provides a summary of the hypotheses, results, findings, and contributions to theory.

**Table 9** Summary of hypotheses and findings

Hypotheses	Experimental Conditions	Results	Findings	Conclusions
H1: Level of stake (low and high) has no influence on the importance of reviews to users  (note: When the reviews are shown to users)	Reviews are shown to users on the webpage in both conditions: Low (1) vs. high-stake (2) trip	Supported	Users read reviews at both levels of stake	When reviews <i>are shown</i> to users on the same webpage, they tend to read them independently of the stake (low and high). Therefore, they form a reputation judgment irrespective of the level of stake since the information is easily accessible
H2: Level of stake (low and high) has an influence on the information cues users access first such that users will access legitimacy-related cues first in low-stake trips and reputation-related cues first in high-stake trips		Supported	In a low-stake trip, users access profile and aggregated ratings score first. In a high-stake trip, users access reviews first	However, the sequence of judgment formation differs between low- and high-stake trips. In low stake, users form a legitimacy judgment first while in high stake, they form a reputation judgment first
H3: In a low-stake trip, the effect of reviews on a user's level of confidence in a (a) host and (b) stay is diminished	Low-stake trip in both conditions: Reviews are not shown to users on the webpage (1) vs. reviews are shown to users on the webpage (2)	Supported	In a low-stake trip, reviews are not essential to users as they mostly rely upon profile and ratings to evaluate a host	In a low-stake trip, when reviews <i>are not shown</i> to users on the same webpage, users' confidence in a host or a stay does not seem to diminish (vs. when the reviews are shown). Also, showing reviews was found to reduce users' intention to book. For a low-stake trip, users do not need to form a reputation judgment to evaluate a host.

## 8. DISCUSSION

Online trust has been instrumental to the growing dominance of online market platforms over traditional incumbents in many services industries, such as hospitality, car sharing and rental,

holidays and travel, and food delivery. The rise of sharing economy platforms has put further emphasis on trust as a necessary condition to enable transactions because users are not institutional actors but private individuals. Unlike institutional actors who may possess characteristics (size of the organization, date of founding, or business license) that legitimate their “right” to operate, private individuals are typically unable to exhibit similar characteristics. Thus, sharing economy platforms have been particularly attentive to providing useful information to help users select trustworthy service providers, though our knowledge of how users process information to make decisions on these platforms is still insufficient. Moreover, the conventional view in information systems literature (Dellarocas, 2010; Jøsang et al., 2007; Zervas et al., 2015) that all the information of a service provider is reputation-based may be inaccurate, as it assumes that users typically go through an intensive cognitive process in their selection tasks for all transactions. Recent development in social judgment literature challenges such a view by suggesting that information on a service provider may relate not only to reputation but also to legitimacy judgment (Bitektine, 2011; Deephouse & Carter, 2005), and that users will resort to one form of social judgment (reputation or legitimacy) depending on the nature of the transaction. In short, the nature of the transaction (high or low stake) determines the form of social judgment users resort to in their evaluation and selection of service providers. This distinction is important because the form of judgment also determines users’ cognitive processes. For example, reputation is associated with intensive cognitive effort, as users collect and process information on the past behavior of a service provider to predict his or her future behavior. By contrast, legitimacy is associated with a routinized cognitive process, as users simply check that a service provider conforms to the minimum standards of the platform and thus has a “license to operate.”

This study investigated users’ selection process of service providers on sharing economy platforms. Specifically, we applied social judgments to explain when users are more likely to

resort to legitimacy or reputation judgment to select service providers. Social judgment literature suggests that the level of stake determines the form of judgment users employ (Bitektine, 2011). In particular, users form legitimacy judgment in low-stake, routinized transactions, as they are unwilling to expend great effort in information search for such low-risk decisions. For high-stake transactions, they are more likely to use reputation judgment, as the higher risk prompts them to assess the service provider's individual characteristics and behavior. In the context of sharing economy platforms, the framework predicts that users rely more on legitimacy judgment for low-stake trips and reputation judgment for high-stake trips. However, our qualitative study revealed that users rely on reviews for host selection regardless of the level of stake, which is counter to the principle of cognitive energy conservation in which users tend to perform judgment task in ways that conserves cognitive energy (Tost, 2011). This intriguing finding may be explained by the facilitated access to reviews on the platform. As all users have access to reviews for all rentals, they expend little or no effort in searching for reputational information cues. Given the availability of information related to a host's reputation, ignoring such information and only relying on legitimating information to select the host would make little sense.

In Experiment 1, we further investigated the findings of the qualitative study by examining the impact of level of stake on users' perceived importance of reviews when the reviews are easily accessible on the webpage of the rental (H1), as it was practiced on Airbnb at the time of the study. We found that users read and value reviews in both low-stake and high-stake trips. Nonetheless, while users perceive reviews to be useful in both low- and high-stake trips, the order of information access vary (H2). Users rely more on profile cues and aggregated ratings scores in low-stake trips, while reviews are prioritized in high-stake trips. This finding suggests users read reviews for all purposes of stay as these are readily available on the webpage of the rental. Yet, the cognitive process was consistent with the literature on

social judgment: legitimacy-related cues were prioritized in the low-stake condition and reputation-related cues were prioritized in the high-stake condition. Given that users formed a legitimacy judgment first in the low-stake condition by processing profile information and aggregated ratings score, we conducted a second experiment to study the usefulness of reviews in low-stake trips by examining the impact of reviews on decision outcomes for this type of transaction (H3). In our second experiment, we did not show the reviews in one of the two conditions and found that users did not express less confidence in the host or the stay when reviews were absent from the pool of information available for a rental. On the contrary, users expressed higher intention to book a rental when presented with profile information and ratings only. In other words, although users tend to read reviews for all trips (low and high stakes) when the reviews are easily accessible, they tend to make more optimal purchase decisions for low-stake trips when the reviews are not accessible. This result points to a potential state of information overload when the platform shows all types of information, including reviews, to users evaluating low-stake trips. Overall, our studies support the view that legitimacy judgment is best suited to users' selection task for low-stake trips while reputation judgment is more appropriate for high-stake trips.

### **8.1 Contributions to Theory**

This study contributes to the understanding of how users process information about service providers to make decisions on sharing economy platforms. Thus, it brings valuable insights to the information systems and management literature. First, the bulk of current work adopts the lens of reputation to investigate how sources of information on both sharing platforms and e-commerce websites can promote trustworthy exchanges (Dellarocas, 2010; Jøsang et al., 2007; Zervas et al., 2015; Zhang, Yan, & Zhang, 2018). Our research suggests that the judgment outcome of this information is not only reputational. Our preliminary quantitative study used FA to confirm this viewpoint by showing that profile data, ratings, and reviews



available on the most popular platforms lead to different forms of judgment—namely, reputation and legitimacy (both cognitive and normative). Incorporating legitimacy sheds light on how users may engage in various cognitive processes and select different types of information to evaluate service providers. The conventional view of reputation as the sole judgment form does not account for the variety of strategies and cognitive processes involved in partner selection tasks. Second, the information systems literature suggests that more information about members helps the platform improve trust by providing a greater amount of information to users (Watt & Wu, 2018). Our findings suggest that this may not be the case, as an increase in the amount and level of information about the host may negatively affect users' decision outcomes. One avenue for future research would be to examine the optimal amount and level of information that should be communicated to users at various stake levels. Finally, despite the enormous growth potential of sharing economy platforms and the growing interest of management scholars for this field of research, we still know very little about how the sharing economy actually operates (Perren & Kozinets, 2018). Although a few studies have elicited the sources of satisfaction and trust on sharing platforms, users' motivations and the mechanisms of platform economics, the behavioral dimensions of users, particularly their decision-making processes, have largely been neglected. Our study is one of the first to unravel some of the mechanisms of selection on sharing economy platforms.

Finally, our results could also be considered from the perspective of the ELM in the persuasion literature (Petty & Cacioppo, 1986). ELM distinguishes two routes of persuasion: a central route whereby persuasion occurs through thorough processing of the available information, and a peripheral route whereby persuasion is induced by cues that are not central to the product's merit. The route to persuasion is typically determined by the level of involvement of consumers, as involvement moderates the amount and type of information processing (Petty, Cacioppo, & Schumann, 1983). Thus, ELM seems to accommodate our

findings well as we show that the level of stake determines whether users first process information that requires a low level of cognitive efforts (legitimacy judgments), or information that requires a high level of cognitive efforts (reputation judgments). Another similarity between our approach informed by social judgment literature and ELM is that the same stimulus can serve as both a peripheral/legitimacy or a central/reputation cue (Miniard, Dickson, & Lord, 1988). For instance, in an advertising persuasion context, the number of message arguments can be used as a peripheral cue if prospective consumers rely on the quantity, rather than on the quality, of message arguments to form an attitude; however, the content of message arguments is used as a central cue if it is carefully scrutinized by prospective consumers to develop an attitude toward the advertised object (Petty & Cacioppo, 1986). Similarly, we suggest that a particular information cue on a platform can be used to form either a legitimacy or a reputation judgment (see Table 1). For example, ratings can be used as a legitimacy cue, if users infer the level of conformance of a host to the quality standards of the platform from aggregated scores, or as a reputation cue, if users rely on specific scores to infer the level of performance of a host on one particular attribute. However, our results differ from those that would be predicted by the ELM as users on sharing economy platforms look at reviews, which requires high cognitive efforts, independently of the level of stake. The ELM would predict that written reviews are not looked at when the level of stake is low. This surprising result may be explained by the fact that reviews are easily accessible on sharing economy platforms independently of the level of stake, therefore sparing users with the cognitive efforts associated with searching for reputational information, as suggested by the results of our first qualitative study. In other words, while the ELM suggests that central and peripheral processing are separate routes (Petty and Cacioppo, 1986), the results of our first experiment suggest that the level of stake does not determine whether users on sharing economy platforms process legitimacy- or reputation-related cues, but how intensively they

process legitimacy- and reputation-related cues: users on sharing economy platform process reputation-related cues independently of the level of stake because such cues are easily accessible; however, whether users access legitimacy- versus reputation-related cues first, and the degree to which they process reputation-related cues is determined by the level of stake. Nonetheless, ELM has received considerable attention over the past four decades, and many individual, situational and product factors have been identified as determinants of the persuasion route. These findings could provide valuable insights for future research on how users process information on sharing economy platforms.

## **8.2 Contributions to Practice**

Our results challenge the common view that users must have access to all information about other users on online marketplaces (see Dellarocas, 2010; Jøsang et al., 2007; Zervas et al., 2015), and thus similar information should be provided to users independently of their motivations in the transaction. Current practices on most sharing economy platforms lean toward providing all available information on service providers to inform decision-making. However, while users tend to read detailed information for all their transactions, this intensive process may be counter-productive, as the amount and level of information exceed their actual needs (Lee & Lee, 2004), and more generally contradicts the principle of cognitive economy which states that users tend to make decisions with minimal cognitive effort (Rescher, 1989). Our findings indicate that users make more efficient decisions when the amount and level of information are adapted to the stake of the transaction. We acknowledge that it is unlikely that platforms hide information to users, and thus, suggest that the different types of information (profiles, ratings, and reviews) are presented in a stepwise manner to help users evaluate hosts and make decisions. For example, the carpooling platform BlaBlaCar first shows a driver's overall rating score and some basic profile information to users who search car-trips. Users can then choose to see detailed rating scores and/or read the reviews about past trips in a next

step. Revealing information in stepwise manner is also practiced by platforms outside of the sharing economy. eBay provides a seller status in search results (e.g., top rated seller), and an overall satisfaction score in percentage and number of reviews on the item's page. Users can also access the written reviews with one more click. We assume that such a system allows users to adapt information depth according to the price of the item (i.e., transaction stake). In conclusion, our recommendations point toward an adaptive system that allows users to modulate the amount and depth of information they need in order to make decisions on partner selection on sharing economy platforms.

#### **8.4 Limitations and future research**

As with many empirical studies, our study has several limitations. First, we used Airbnb as the case for our study. Although the different types of information cues on Airbnb are also present in similar forms on other popular sharing economy platforms (e.g., BlaBlaCar), our findings may not be generalizable to other sharing platforms. In addition, we have no certainty that our model will generalize beyond sharing platforms and we welcome future studies to build on our findings to examine user evaluation process on traditional e-commerce platforms, such as eBay or Amazon, which combine several transaction types (B2C and C2C). Second, although we unraveled some of the mechanisms of judgment formation from different types of information cues in the selection of service providers, our study did not examine how the two forms of judgment (legitimacy and reputation) interact and complement each other in affecting selection outcomes in long-term decisions. We encourage scholars to examine how the two forms of judgment may interact, switch, and complement each other in a longitudinal study where judgments evolve over time, especially when trips are high stake. This limitation did not affect our findings as our study was not longitudinal. Future studies may also further our findings by exploring the impact of transaction stake on partner selection on a continuous spectrum. This approach would bring more accurate insights into the

relationship between level of stake and importance of reviews in user's decision-making process. Another avenue for future research is to look at how review contents may affect the evaluative behavior of users on sharing economy platforms. Although the volume of reviews may lead to information overload for simple selection tasks, it would be interesting to examine what type of review contents are more likely to produce information overload. For instance, Schneider (1987, p. 144) stated that overload takes place when "the nature of the information is differentiated in terms of uncertainty, ambiguity or equivocality, novelty, complexity and intensity." An interesting focus would be the notion of ambiguity, described as when the same information can be interpreted in different ways and has unclear meaning. Given that sharing economy users are often private individuals who use the platform occasionally, we may expect that some of the written reviews may contain ambiguous comments. The structure of a review may also be associated with information overload (Lurie, 2004), for example, when a review lists a long series of details on the product or service. The suggestions above may be interesting avenues to complement our findings. Furthermore, in complement to legitimacy and reputation, status as a judgment form may also be an interesting topic in sharing economy. For instance, status represents the relative position of an individual in a network of actors (Rindova, Pollock, & Hayward, 2006), and thus may also affect user decision outcomes on sharing platforms that rank service providers. Nevertheless, since status is socially constructed and inter-subjectively agreed upon (Washington & Zajac, 2005), scholars should consider rankings of service providers that are community-based. Finally, our results are bounded by the geographic delimitation of the United Kingdom and possibly the cultural context of Western economies. However, the development of sharing platforms is global, and the literature on inter-cultural management suggests that users with different cultural background are likely to behave differently on sharing platforms. This is another promising avenue for future research.

## References

- Acquier, A., Carbone, V., & Massé, D. (2016). *Farming the sharing economy: A business model perspective*. Paper presented at the EGOS, Napoli.
- Ahlstrom, D., & Bruton, G. D. (2001). Learning from successful local private firms in China: Establishing legitimacy. *The Academy of Management Executive*, 15(4), 72-83.
- Aldrich, H. E., & Fiol, C. M. (1994). Fools rush in? The institutional context of industry creation. *Academy of management Review*, 19(4), 645-670.
- Alexiou, K., & Wiggins, J. (2019). Measuring individual legitimacy perceptions: Scale development and validation. *Strategic Organization*, 17(4), 470-496.
- Baek, H., Ahn, J., & Choi, Y. (2012). Helpfulness of Online Consumer Reviews: Readers' Objectives and Review Cues. *International Journal of Electronic Commerce*, 17(2), 99-126. doi: 10.2753/JEC1086-4415170204
- Belk, R. (2014). You are what you can access: Sharing and collaborative consumption online. *Journal of Business Research*, 67( 8), 1595-1600.
- Bitektine, A. (2011). Toward a theory of social judgments of organizations: The case of legitimacy, reputation, and status. *Academy of management Review*, 36(1), 151-179.
- Chaiken, S. (1987). *The heuristic model of persuasion*. Paper presented at the Social influence: the ontario symposium.
- Chaiken, S., & Ledgerwood, A. (2011). A theory of heuristic and systematic information processing. *Handbook of theories of social psychology: Volume one*, 246-166.
- Chang, M. K., Cheung, W., & Tang, M. (2013). Building trust online: Interactions among trust building mechanisms. *Information & Management*, 50(7), 439-445.
- Chasin, F., von Hoffen, M., Cramer, M., & Matzner, M. (2018). Peer-to-peer sharing and collaborative consumption platforms: a taxonomy and a reproducible analysis. *Information Systems and e-Business Management*, 16(2), 293-325.
- Cheng, X., Fu, S., Sun, J., Bilgihan, A., & Okumus, F. (2019). An investigation on online reviews in sharing economy driven hospitality platforms: A viewpoint of trust. *Tourism Management*, 71, 366-377.
- Cui, R., Li, J., & Zhang, D. J. (2020). Reducing discrimination with reviews in the sharing economy: Evidence from field experiments on Airbnb. *Management Science*, 66(3), 1071-1094.
- Cusumano, M. A. (2015). How traditional firms must compete in the sharing economy. *Communications of the ACM*, 58(1), 32-34.
- Deephouse, D. L., & Carter, S. M. (2005). An examination of differences between organizational legitimacy and organizational reputation. *Journal of Management Studies*, 42(2), 329-360.
- Dellarocas, C. (2010). Online reputation systems: How to design one that does what you need. *MIT Sloan management review*, 51(3), 33-38.
- Dogru, T., Mody, M., Suess, C., McGinley, S., & Line, N. D. (2020). The Airbnb paradox: Positive employment effects in the hospitality industry. *Tourism Management*, 77, 104001.
- Ene, D., & Schofield, P. (2011). An integrated approach to consumer decision making for budget city breaks: the role of emotion. *International Journal of Tourism Research*, 13(4), 368-383.
- Ert, E., Fleischer, A., & Magen, N. (2016). Trust and reputation in the sharing economy: The role of personal photos in Airbnb. *Tourism Management*, 55, 62-73.
- Gao, J., Zhang, C., Wang, K., & Ba, S. (2012). Understanding online purchase decision making: The effects of unconscious thought, information quality, and information quantity. *Decision Support Systems*, 53(4), 772-781. doi: <https://doi.org/10.1016/j.dss.2012.05.011>
- Ghose, A., Ipeiritos, P. G., & Li, B. (2014). Examining the impact of ranking on consumer behavior and search engine revenue. *Management Science*, 60(7), 1632-1654.
- Gibbs, C., Guttentag, D., Gretzel, U., Morton, J., & Goodwill, A. (2018). Pricing in the sharing economy: a hedonic pricing model applied to Airbnb listings. *Journal of Travel & Tourism Marketing*, 35(1), 46-56.

- Gonzalez-Padron, T. L. (2017). Ethics in the sharing economy: Creating a legitimate marketing channel. *Journal of Marketing Channels*, 24(1-2), 84-96.
- Greenwood, B. N., & Wattal, S. (2017). Show me the way to go home: an empirical investigation of ride-sharing and alcohol related motor vehicle fatalities. *MIS quarterly*, 41( 1), 163-187.
- Grégoire, D. A., Binder, J. K., & Rauch, A. (2019). Navigating the validity tradeoffs of entrepreneurship research experiments: A systematic review and best-practice suggestions. *Journal of business venturing*, 34(2), 284-310.
- Guyader, H. (2018). No one rides for free! Three styles of collaborative consumption. *Journal of Services Marketing*, 32(6), 692-714.
- Hamari, J., Sjöklint, M., & Ukkonen, A. (2016). The sharing economy: Why people participate in collaborative consumption. *Journal of the association for information science and technology*, 67(9), 2047-2059.
- Hu, H.-f., & Krishen, A. S. (2019). When is enough, enough? Investigating product reviews and information overload from a consumer empowerment perspective. *Journal of Business Research*, 100, 27-37.
- Huang, Q., Davison, R. M., & Liu, H. (2014). An exploratory study of buyers' participation intentions in reputation systems: The relationship quality perspective. *Information & Management*, 51(8), 952-963.
- Jones, K., & Leonard, L. N. (2008). Trust in consumer-to-consumer electronic commerce. *Information & Management*, 45(2), 88-95.
- Jordan, E. J., & Moore, J. (2018). An in-depth exploration of residents' perceived impacts of transient vacation rentals. *Journal of Travel & Tourism Marketing*, 35(1), 90-101.
- Jøsang, A., Ismail, R., & Boyd, C. (2007). A survey of trust and reputation systems for online service provision. *Decision support systems*, 43(2), 618-644.
- King, B. G., & Whetten, D. A. (2008). Rethinking the relationship between reputation and legitimacy: A social actor conceptualization. *Corporate Reputation Review*, 11(3), 192-207.
- Knofczynski, G. T., & Mundfrom, D. (2008). Sample sizes when using multiple linear regression for prediction. *Educational and psychological measurement*, 68(3), 431-442.
- Kostyk, A., Niculescu, M., & Leonhardt, J. M. (2017). Less is more: Online consumer ratings' format affects purchase intentions and processing. *Journal of Consumer Behaviour*, 16(5), 434-441. doi: 10.1002/cb.1643
- Kraatz, M. S., & Block, E. S. (2008). Organizational implications of institutional pluralism. *The Sage handbook of organizational institutionalism*, 840, 243-275.
- Kruglanski, A. W. (2001). Motivation and social cognition: Enemies or a love story? . *International Journal of Psychology and Psychological Therapy*, 1(1), 33-45.
- Kuksov, D., & Villas-Boas, J. M. (2010). When more alternatives lead to less choice. *Marketing Science*, 29(3), 507-524.
- Kumar, V., Lahiri, A., & Dogan, O. B. (2018). A strategic framework for a profitable business model in the sharing economy. *Industrial Marketing Management*, 69, 147-160.
- Lange, D., Lee, P. M., & Dai, Y. (2011). Organizational reputation: A review. *Journal of management*, 37(1), 153-184.
- Lawrence, T. B. (1998). Examining resources in an occupational community: Reputation in Canadian forensic accounting. *Human Relations*, 51(9), 1103-1131.
- Lee, B. K., & Lee, W. N. (2004). The effect of information overload on consumer choice quality in an on-line environment. *Psychology & Marketing*, 21(3), 159-183.
- Lee, H., Yang, S.-B., & Koo, C. (2019). Exploring the effect of Airbnb hosts' attachment and psychological ownership in the sharing economy. *Tourism Management*, 70, 284-294.
- Lee, S.-H., Lee, B.-Y., & Kim, H.-W. (2019). Decisional factors leading to the reuse of an on-demand ride service. *Information & Management*, 56(4), 493-506.
- Leung, X. Y., Xue, L., & Wen, H. (2019). Framing the sharing economy: Toward a sustainable ecosystem. *Tourism Management*, 71, 44-53.

- Li, H., Fang, Y., Lim, K. H., & Wang, Y. (2019). Platform-Based Function Repertoire, Reputation, and Sales Performance of E-Marketplace Sellers. *MIS quarterly*, 43(1), 207-236.
- Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry* (vol. 75): Sage Thousand Oaks, CA.
- Luo, X. (2002). Trust production and privacy concerns on the Internet A framework based on relationship marketing and social exchange theory. *Industrial Marketing Management*, 31(2), 111-118.
- Lurie, N. H. (2004). Decision making in information-rich environments: The role of information structure. *Journal of consumer research*, 30(4), 473-486.
- Mahadevan, R. (2018). Examination of motivations and attitudes of peer-to-peer users in the accommodation sharing economy. *Journal of Hospitality Marketing & Management*, 27(6), 679-692.
- Mair, J., & Reischauer, G. (2017). Capturing the dynamics of the sharing economy: Institutional research on the plural forms and practices of sharing economy organizations. *Technological Forecasting and Social Change*, 125, 11-20.
- Malhotra, N. K. (1984). Reflections on the information overload paradigm in consumer decision making. *Journal of consumer research*, 10(4), 436-440.
- Marchi, A., & Parekh, E.-J. (2015). *How the sharing economy can make its case*. New York: McKinsey.
- Mehra, A., Dixon, A. L., Brass, D. J., & Robertson, B. (2006). The social network ties of group leaders: Implications for group performance and leader reputation. *Organization science*, 17(1), 64-79.
- Miniard, P. W., Dickson, P. R., & Lord, K. R. (1988). Some central and peripheral thoughts on the routes to persuasion. *ACR North American Advances*.
- Mishina, Y., Block, E. S., & Mannor, M. J. (2012). The path dependence of organizational reputation: How social judgment influences assessments of capability and character. *Strategic management journal*, 33(5), 459-477.
- Mittendorf, C., Berente, N., & Holten, R. (2019). Trust in sharing encounters among millennials. *Information Systems Journal*, 29(5), 1083-1119.
- Möhlmann, M. (2015). Collaborative consumption: determinants of satisfaction and the likelihood of using a sharing economy option again. *Journal of Consumer Behavior*, 14(3), 193-207.
- Moon, Y. (2015). Uber: Changing the way the world moves. *Harvard Business School, Case*, 101.
- Muñoz, P., & Cohen, B. (2017). Mapping out the sharing economy: A configurational approach to sharing business modeling. *Technological Forecasting and Social Change*, 125, 21-37.
- Nakagawa, S., & Cuthill, I. C. (2007). Effect size, confidence interval and statistical significance: a practical guide for biologists. *Biological reviews*, 82(4), 591-605.
- Ozanne, L. K., & Ballantine, P. W. (2010). Sharing as a form of anti-consumption? An examination of toy library users. *Journal of Consumer Behaviour*, 9, 485-498.
- Ozanne, L. K., & Ballantine, P. W. (2010). Sharing as a form of anti-consumption? An examination of toy library users. *Journal of Consumer Behaviour*, 9(6), 485-498.
- Parguel, B., Lunardo, R., & Benoit-Moreau, F. (2017). Sustainability of the sharing economy in question: When second-hand peer-to-peer platforms stimulate indulgent consumption. *Technological Forecasting and Social Change*, 125, 48-57.
- Perren, R., & Kozinets, R. V. (2018). Lateral exchange markets: how social platforms operate in a networked economy. *Journal of Marketing*, 82(1), 20-36.
- Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion *Communication and persuasion* (pp. 1-24): Springer.
- Petty, R. E., Cacioppo, J. T., & Schumann, D. (1983). Central and peripheral routes to advertising effectiveness: The moderating role of involvement. *Journal of consumer research*, 10(2), 135-146.
- Prabhu, J., & Stewart, D. W. (2001). Signaling strategies in competitive interaction: Building reputations and hiding the truth. *Journal of Marketing Research*, 38(1), 62-72.



- Prayag, G., & Ozanne, L. K. (2018). A systematic review of peer-to-peer (P2P) accommodation sharing research from 2010 to 2016: progress and prospects from the multi-level perspective. *Journal of Hospitality Marketing & Management*, 27(6), 649-678.
- Rescher, N. (1989). *Cognitive economy: The economic dimension of the theory of knowledge*: University of Pittsburgh Pre.
- Richins, M. L. (1983). Negative word-of-mouth by dissatisfied consumers: A pilot study. *Journal of marketing*, 47(1), 68-78.
- Rindova, V. P., Pollock, T. G., & Hayward, M. L. (2006). Celebrity firms: The social construction of market popularity. *Academy of management Review*, 31(1), 50-71.
- Rindova, V. P., Williamson, I. O., Petkova, A. P., & Sever, J. M. (2005). Being good or being known: An empirical examination of the dimensions, antecedents, and consequences of organizational reputation *Academy of Management Journal*, 48(6), 1033–1049.
- Rothschild, M. L. (1984). Perspectives on involvement: current problems and future directions. *ACR North American Advances*.
- Rotter, J. B. (1967). A new scale for the measurement of interpersonal trust 1. *Journal of personality*, 35(4), 651-665.
- Scaraboto, D. (2015). Selling, Sharing, and Everything In Between: The Hybrid Economies of Collaborative Networks. *Journal of consumer research*, 42( 1), 152–176.
- Schneider, S. C. (1987). Information overload: Causes and consequences. *Human Systems Management*, 7(2), 143-153.
- Scott, W. R. (1995). *Institutions and organizations*. Thousand Oak, CA: Sage.
- Scott, W. R. (2013). *Institutions and organizations: Ideas, interests, and identities*: Sage publications.
- Sherif, M., & Hovland, C. I. (1961). Social judgment: Assimilation and contrast effects in communication and attitude change.
- Singh, J. P., Irani, S., Rana, N. P., Dwivedi, Y. K., Saumya, S., & Kumar Roy, P. (2017). Predicting the “helpfulness” of online consumer reviews. *Journal of Business Research*, 70(Supplement C), 346-355. doi: <https://doi.org/10.1016/j.jbusres.2016.08.008>
- Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of management Review*, 20(3), 571-610.
- Sutherland, W., & Jarrahi, M. H. (2018). The sharing economy and digital platforms: A review and research agenda. *International Journal of Information Management*, 43, 328-341.
- Tadelis, S. (2016). Reputation and feedback systems in online platform markets. *Annual Review of Economics*, 8, 321-340.
- Tost, L. P. (2011). An integrative model of legitimacy judgments. *Academy of management Review*, 36(4), 686-710.
- Tseng, Y.-C., & Chan, C.-L. (2019). When the Sharing Economy Meets Established Institutions: Uber and Airbnb in Taiwan. *IEEE Transactions on Engineering Management*.
- Tussyadiah, I. P., & Park, S. (2018). When guests trust hosts for their words: Host description and trust in sharing economy. *Tourism Management*, 67, 261-272.
- Uzunca, B., Rigtering, J. C., & Ozcan, P. (2018). Sharing and shaping: A cross-country comparison of how sharing economy firms shape their institutional environment to gain legitimacy. *Academy of management discoveries*, 4(3), 248-272.
- VanVoorhis, C. W., & Morgan, B. L. (2007). Understanding power and rules of thumb for determining sample sizes. *Tutorials in quantitative methods for psychology*, 3(2), 43-50.
- Venkatesh, V., Brown, S. A., & Bala, H. (2013). Bridging the qualitative-quantitative divide: Guidelines for conducting mixed methods research in information systems. *MIS quarterly*, 21-54.
- Venkatesh, V., Brown, S. A., & Sullivan, Y. W. (2016). Guidelines for conducting mixed-methods research: An extension and illustration. *Journal of the Association for Information Systems*, 17(7), 2.
- Washington, M., & Zajac, E. J. (2005). Status evolution and competition: Theory and evidence. *Academy of Management Journal*, 48(2), 282-296.

- Watt, M., & Wu, H. (2018). *Trust mechanisms and online platforms: A regulatory response*. M-RCBG Associate Working Paper Series No. 97.
- Weber, T. A. (2014). Intermediation in a sharing economy: insurance, moral hazard, and rent extraction. *Journal of Management Information Systems*, 31(3), 35–71.
- Weber, T. A. (2016). Product pricing in a peer-to-peer economy. *Journal of Management Information Systems*, 33(2), 573-596.
- Weigelt, K., & Camerer, C. (1988). Reputation and corporate strategy: A review of recent theories. . *Strategic Management Journal*, 9, 443-454.
- Wu, L.-L., & Lin, J.-Y. (2006). The quality of consumers' decision-making in the environment of e-commerce. *Psychology and Marketing*, 23(4), 297-311. doi: 10.1002/mar.20112
- Wu, L.-L., & Lin, J.-Y. (2012). The Match between Information Control and Motivation in the Online Context. *Psychology & Marketing*, 29(11), 822-835. doi: 10.1002/mar.20567
- Yamauchi, T., & Yu, N. (2008). Category labels versus feature labels: Category labels polarize inferential predictions. *Memory & Cognition*, 36(544–553).
- Yang, S.-B., Lee, H., Lee, K., & Koo, C. (2018). The application of Aristotle's rhetorical theory to the sharing economy: an empirical study of Airbnb. *Journal of Travel & Tourism Marketing*, 35(7), 938-957.
- Yang, Y., & Mao, Z. (2019). Welcome to my home! An empirical analysis of Airbnb supply in us cities. *Journal of Travel Research*, 58(8), 1274-1287.
- Ye, S., Gao, G., & Viswanathan, S. (2014). Strategic behavior in online reputation systems: evidence from revoking on ebay. *MIS quarterly*, 38(4), 1033-1056.
- Ye, S., Viswanathan, S., & Hann, I.-H. (2018). The value of reciprocity in online barter markets: an empirical investigation. *MIS quarterly*, 42(2), 521-549.
- Zaichkowsky, J. L. (1994). The personal involvement inventory: Reduction, revision, and application to advertising. *Journal of advertising*, 23(4), 59-70.
- Zervas, G., Proserpio, D., & Byers, J. (2015). A first look at online reputation on Airbnb, where every stay is above average. *Working paper*.
- Zervas, G., Proserpio, D., & Byers, J. W. (2017). The rise of the sharing economy: Estimating the impact of Airbnb on the hotel industry. *Journal of Marketing Research*, 54(5), 687-705.
- Zhang, L., Yan, Q., & Zhang, L. (2018). A computational framework for understanding antecedents of guests' perceived trust towards hosts on Airbnb. *Decision Support Systems*, 115, 105-116.
- Zhang, S., Zhao, L., Lu, Y., & Yang, J. (2016). Do you get tired of socializing? An empirical explanation of discontinuous usage behaviour in social network services. *Information & Management*, 53(7), 904-914.
- Zhang, Z., Ye, Q., Law, R., & Li, Y. (2010). The impact of e-word-of-mouth on the online popularity of restaurants: A comparison of consumer reviews and editor reviews. *International Journal of Hospitality Management*, 29(4), 694-700.
- Zimmerman, M. A., & Zeitz, G. J. (2002). Beyond survival: Achieving new venture growth by building legitimacy. *Academy of management Review*, 27(3), 414-431.