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First vs. Lasting Impressions: How Cognitive and Affective Trust Cues Coordinate Match-Making in Online Sharing Platforms

Timm Teubner[1] · David Dann[2] · Florian Hawlitschek[1] · Mareike Möhlmann[3]

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Abstract

Digital platforms facilitate the coordination, match making, and value creation for large groups of individuals. In consumer-to-consumer (C2C) online sharing platforms specifically, trust between these individuals is a central concept in determining which individuals will eventually engage in a transaction. The majority of today's online platforms draw on various types of cues for group coordination and trust building among users. Current research widely accepts the capacity of such cues but largely ignores their changing effectiveness over the course of a user's lifetime on the platform. To address this gap, we conduct a laboratory experiment, studying the interplay of cognitive and affective trust cues over the course a multi-period trust experiment for the coordination of groups. We find that the trust-building capacity of affective trust cues is time-dependent and follows an inverted u-shape form, suggesting a dynamic complementarity of cognitive and affective trust cues.

Keywords Online sharing platforms · Reputation systems · Trust cues · Lab experiment

✉ Timm Teubner
teubner@tu-berlin.de

David Dann
david.dann@kit.edu

Florian Hawlitschek
hawlitschek@campus.tu-berlin.de

Mareike Möhlmann
mmoehlmann@bentley.edu

[1] Einstein Center Digital Future, TU Berlin, Straße des 17. Juni, 10623 Berlin, Germany

[2] Insitute for Information Systems and Marketing, Karlsruhe Institute of Technology, Kaiserstraße 89, 76133 Karlsruhe, Germany

[3] Department of Computer Information Systems, Bentley University, Smith Technology Center 409, Waltham, MA 02452, USA

1 Introduction

Digital market platforms critically depend on mechanisms of group coordination, that is, matching the different sides–typically supply and demand (Bui et al. 2006; Dann et al. 2020; Lusch and Nambisan 2015; Ströbel and Stolze 2002). As "posting services [on digital market platforms] does not […] necessarily lead to market transactions" (Bui et al. 2006, p. 469), platforms facilitate coordination and the ensuing value creation for large groups of individuals. Trust between individuals is a central concept for whether or not group coordination, collaboration, and transactions will eventually take place (Cheng et al. 2021; Cheng and Macaulay 2014; Engelmann et al. 2022; Lai and Turban 2008; Teubner and Camacho 2023). Consumer-to-consumer (C2C) platforms represent a very successful and fast-growing business model (Gawer 2014; Mittendorf et al. 2019; Saadatmand et al. 2019; Sundararajan 2016; Zimmermann et al. 2018). For instance, the accommodation sharing platform Airbnb was only founded in 2007 but has, as of now, more than 4 million active users and facilitated over 1.4 billion stays (Airbnb 2023). For such platforms, creating and maintaining trust among users is one of the most crucial endeavors for the coordination and realization of transactions (Dann et al. 2019; Jensen et al. 2015; Möhlmann 2021; Teubner et al. 2021; Teubner and Camacho 2023). Platforms can create trust between users by implementing different types of mechanisms (Nicolaou and McKnight 2006). Beyond cognitive trust cues such as (numerical) ratings, affective trust cues engender trust through emotions (Komiak and Benbasat 2006; Stewart and Gosain 2006) and the probably most widely-used example are profile photos (Ert et al. 2016; Riedl et al. 2014).

Previous research builds on the implicit assumption that antecedents of trust have relatively stable effects (McKnight et al. 1998, 2002a) while little is known about how the effectiveness of trust cues holds up *over time,* that is when being applied again and again (Möhlmann 2021). Especially new users face the dilemma of limited credibility (i.e., an empty track record), which impedes their ability to transact (and hence to build a track record). Surprisingly, most previous research on trust cues in online platforms take snap-shot perspectives and have not yet addressed dynamic trust perceptions over the course of time (Cabral and Hortaçsu 2010; McKnight et al. 1998, 2002a). We hence ask:

How do cognitive and affective trust cues affect trusting behavior over time—and how do they complement each other?

To address this research question, we build on insights from the Elaboration Likelihood Model (ELM) on information processing (Petty and Cacioppo 1986; Petty et al. 1983) and apply it in the context of trust research. We conduct a controlled laboratory experiment, investigating trusting behavior across several interactions with varying counterparts. Previous research into rating systems (Abrahao et al. 2017; Banerjee et al. 2017; Cheng et al. 2019) and profile photos (Ert et al. 2016; Fagerstrøm et al. 2017) has commonly conceptualized trust through self-reported scales on (hypothetical) intentions. While such approaches have undoubtedly informed our understanding of trust within online market places, they have not considered the emergence of trusting behavior across several interactions. To capture trust behavior over time, we hence conduct an experiment in which participants are incentivized by monetary outcomes and interact within a controlled peer-to-peer platform environment.

In line with a large body of experimental research (Blue et al. 2020; Ewing et al. 2019; Gefen et al. 2008), we operationalize trust as the exhibited behavior in an adapted version of Berg et al. (1995)'s seminal trust game. Thereby, we extend the original experiment with multiple periods and *endogenous* match-making (i.e., participants decide on whom to interact with themselves), where participants take the role of consumers or providers. Specifically, we employ a 2 (reputation system: provided/not provided) × 2 (profile photos: provided/not provided) between-subjects design. Further, our experimental design reflects that (1) peer-to-peer matches occur endogenously as the result of a market-based requests-and-response process and (2) exchanges create (economic) exposure for both sides (e.g., risk of fraud, theft, verbal/physical violence, privacy invasions, etc.). Although the risk of worst-case scenarios is commonly considered very low, the list of reported incidents is long (AirbnbHell 2023).

We contribute to trust research in multiple ways (Gawer 2014; Lucas et al. 2021; Möhlmann 2021). Our starting point is previous trust research that builds on the implicit assumption that the effects of trust cues are time-invariant (McKnight et al. 1998, 2002a) and increase with quality and quantity (Cabral and Hortaçsu 2010). In contrast to this, we challenge existing stability assumptions, putting forward that trust cues may be less stable and hence have temporary effects (Bhattacherjee and Sanford 2006; Petty and Cacioppo 1986; Petty et al. 1983). Indeed, our findings indicate that the trust-building capacity of cognitive trust cues is very limited initially but increases steadily, while affective trust cues start out from a higher level and follow an inverted u-shape form over time. We argue that affective trust cues may hence serve as a powerful complement in early stages of platform evolution and may thus help to overcome the inherent "cold start problem" of platforms in general and the users thereon in particular (Wessel et al. 2017).

2 Theoretical Background

2.1 Elaboration Likelihood Model (ELM)

When applied in the context of trust research, the Elaboration Likelihood Model (ELM) on information processing (Petty and Cacioppo 1986; Petty et al. 1983) challenges the assumption that in-the-moment snap-shots are adequate to sufficiently capture the dynamics of trust and how they may play out over time. Petty and colleagues distinguish two different routes of information processing–the central and the peripheral route. The central route refers to changes in attitudes resulting from an individual's cognitive considerations of the information's actual quality, such as a careful calculation of costs and benefits (e.g., Bhattacherjee and Sanford 2006). Second, the peripheral route to attitude change is not based on extensive contemplation about the issue at hand, but the mode of evaluation relies on affective conclusions drawn from intuitive impulses and impressions (Chang et al. 2020; Cyr et al. 2018). ELM researchers theorize that changes of attitudes associated with the peripheral route of information processing are (more) temporary and less predictable (Petty and Cacioppo 1986; Petty et al. 1983), as they are less stable over time (Bhattacherjee and Sanford 2006).

Surprisingly, previous trust research has not addressed potential temporary and unpredictable perceptions about trust cues processed via the peripheral route over the course of time yet. These seem to challenge well-established assumptions made about rather stable and predictable (McKnight et al. 1998, 2002b) or steadily increasing (Cabral and Hortaçsu 2010) effects of trust cues on trust as communicated in previous research.

2.2 Star Ratings as Cognitive Trust Cues

Cognitive trust cues instigate a process of calculative reasoning and reputation systems are a prime example of such cues (Chen et al. 2015; Mishra et al. 1998). On peer-to-peer online platforms, users typically interact with transaction partners that they have never met or interacted with before (Teubner 2018). Thus, users cannot build a history of personal interaction or gain first-hand experience of others' trustworthiness. Reputation systems help to overcome this gap by enabling access to another user's past behaviors (Bolton et al. 2013; Mazzella et al. 2016; Mohan 2019; Möhlmann 2021).[1] This track record, in turn, sets expectations and reduces uncertainty about future behaviors, for instance, regarding whether a product or service will be delivered as promised, or about an individual's amicability, mindfulness, or integrity.

Based on the work by McKnight et al. (1998, p. 476), we associate star ratings with the central route of information processing as discussed in the ELM (Petty and Cacioppo 1986; Petty et al. 1983). In their model on the initial formation of trust, McKnight et al. (1998) theorize knowledge about reputation to be a cognitive process. Star ratings are arguably the most widely-used type of trust cue and are employed in some form by most consumer platforms (Dann et al. 2020; Hesse et al. 2020; Mohan 2019; Schoenmüller et al. 2018). Star rating scores evolve over time as they represent the aggregation of feedback from continuous transactions with ever-varying partners (Ba and Pavlou 2002; Dellarocas 2006; Rice 2012). To avoid the risk of collusion or retaliation, these systems commonly follow a simultaneous evaluation process, in which ratings are only revealed after both parties have submitted their evaluations (Fradkin et al. 2018). Consequently, a user's average rating score serves as a quantified proxy of their trustworthiness based on their overall (past) behavior on the platform. Indeed, positive ratings are a driver for demand (Ert et al. 2016) and allow users to enforce higher prices (Gan and Wang 2017; Gibbs et al.

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

2017). Rice (2012) showed that, while the mere existence of a numerical rating system encourages participants to engage in the market at all, the specific information conveyed by the ratings facilitates transactions among them.

One well-established assumption made in prior research addressing reputation, which we associate with the central route of information processing as introduced in the ELM (Petty and Cacioppo 1986; Petty et al. 1983), is that trust is rather stable (McKnight et al. 1998), and steadily increasing *over time* (Cabral and Hortaçsu 2010). Rating systems are used to build and maintain trust in various contexts (Dellarocas 2003; Mohan 2019). We argue that in the context of peer-to-peer platforms, star ratings can be considered as persuasive messages of high personal relevance. In absence of strong distractions, deliberately processing a message's content is likely and will lead to behavioral change—that is, trusting behavior (Petty and Cacioppo 1986) where the cue's strength directly impacts persuasion outcomes (Kim and Benbasat 2009). Updating a star rating periodically (through additional transactions) improves it continuously in terms of reliability by reducing the potential impact of fraudulent, shill, or erroneous reviews (Rice 2012; Tadelis 2016). Numerical rating systems are hence likely to become more reliable and functional for increasing numbers of completed transactions. Thus, we expect that the influence of continuously updated star ratings will result in an increasing effect on trusting behavior over time.

H_1: *The effect of star ratings on trusting behavior in peer-to-peer sharing transactions increases over time.*

2.3 Profile Photos as Affective Trust Cues

Profile photos are one of the most common affective trust cues in online settings and the human brain processes faces intuitively and subliminally (Kanwisher et al. 1997). Research identified the so-called *fusiform face area* as being "selectively involved in the perception of faces" (Kanwisher et al. 1997, p. 4302). This human tendency to process faces is genetically encoded (Anzellotti and Caramazza 2014). Already infants react to faces within the first minutes after birth (Goren et al. 1975)–the process is hence not socially or culturally learned. Also, detecting facial expressions happens unconsciously and fast (i.e., in the magnitude of milliseconds) (Willis and Todorov 2006). Affective trust cues such as photos are hence processed without deliberate consideration. For this reason, we associate profile photos with the *peripheral* route of information processing (Petty and Cacioppo 1986; Petty et al. 1983). The effects associated with this route are considered to be less stable over time (Bhattacherjee and Sanford 2006).

Notably, trust-building is not solely a calculative process but also involves emotions (Komiak and Benbasat 2006). At the same time, human behavior can be emotional, spontaneous, and impulsive, rendering affective trust cues pivotal for trust formation. Profile photos in online environments showing human faces are hence bound to trigger emotion (Komiak and Benbasat 2006).

The underlying basic effect of photographs on trust can be explained through various theoretical frameworks. For instance, *Social Presence Theory* (Cyr et al.

2007; Gefen and Straub 2004; Hess et al. 2009; Lowry et al. 2010) suggests that the extent to which a person's online presence resembles their real-world presence affects how others perceive and trust them. When a profile includes an actual face, it adds a human element to the online interaction, making the person seem more real and relatable. This perceived "social presence" can enhance trust because it feels like you are interacting with a genuine individual rather than an anonymous entity. Moreover, *Social Identity Theory* (Güth et al. 2008; Tanis and Postmes 2005) suggests that people tend to trust others who they perceive as part of their in-group or sharing similar characteristics. When a profile photo includes an actual face, it *humanizes* the individual and allows viewers to associate them with a real person. This can lead to a stronger sense of connection and trust, as the person appears to be more relatable and potentially part of the same social or cultural group. Also, the *Mere Exposure Effect* (Bornstein and D'Agostino 1992) suggests that people tend to develop a preference for things they are exposed to repeatedly. When you see someone's actual face in their profile photo, you become more familiar with them over time, even in the online context. This increased familiarity can lead to a greater sense of trust, as you feel like you "know" the person better. Naturally, the notion of anonymity reduction may also play a role here. By disclosing a personal profile photo, users may provide hints regarding their sex, ethnicity, approximate age, and lifestyle–that is to say, their personal identity. Online environments usually come with a considerable degree of anonymity, which can lead to distrust due to the potential for deceit or misrepresentation. However, when a person includes their actual face in their profile photo, it reduces anonymity to some extent. This can signal a willingness to be more transparent and accountable for one's actions, which can–in turn–foster trust (Cyr et al. 2009; Gefen and Straub 2003, 2004; Hassanein and Head 2007; Ou et al. 2014), especially in computer-mediated communication such as in electronic commerce or online social networks (Qiu and Benbasat 2010; Steinbrück et al. 2002). Last, a genuine profile photo, especially when it appears unaltered or not overly staged, can serve as a cue of authenticity. As people are likely to trust others who they perceive as being truthful and honest, when a profile photo shows a real face, it can signal that the person is not hiding behind a mask or using a fake identity and hence engender trust.

The trust-promoting effects of human images and profile photos on trust have been confirmed in various settings, including various platforms (Cyr et al. 2009; Ert et al. 2016; Teubner 2022; Teubner et al. 2022). It is hence not surprising that most user-centered online services and platforms offer customizable profiles, and the majority of (if not all) users make use of this feature (Ert et al. 2016; Fagerstrøm et al. 2017; Hesse et al. 2020). In fact, many platform operators actively encourage their users to upload a profile photo when setting up an account. The ride sharing platform BlaBlaCar even provides a search option allowing users to filter rides based on the condition that the driver has uploaded a photo and claims that on average, users with a photo are contacted three times more often than those without a photo (BlaBlaCar 2022).

As the context of peer-to-peer sharing puts a particular focus on the perception of profile photos, we argue that the processing of these affective cues will lead to an effect on trusting behavior. We expect that profile photos will be processed as affective trust cues through the peripheral route. However, since profile photos convey no persuasive argument per se, they will trigger "relatively primitive affective states" (Petty and Cacioppo 1986) such as the perception of social presence. This state is associated with a positive effect on trusting behavior but–as we hypothesize here–the effect decreases over time. This is for mainly two reasons. First, while some measures of attitude can be remarkably stable (e.g., toward a political party), trusting attitudes such as here may be prone to decay (Bhattacherjee and Sanford 2006; Petty et al. 2009). Since–in contrast to star ratings–the informational value of profile photos does not change (hence: not increase) over time, their impact can be expected to "wear off" simply due to habituation and the assumption of profile photos as a given (i.e., familiarity and desensitization). Second, while ratings represent (a presumably) objective measure of past behavior (i.e., a strong signaling device and hence a hard currency for trust building), the interpretation of photos (i.e., much softer cues) is more susceptible to counterarguments (Petty and Cacioppo 1986). For instance, over time, people are likely to have subpar experiences such as low quality or exploitative behavior. As by the nature of photos as weak signaling devices, these are bound to occur for any photo condition. While, in general, negative experiences are quite rare on most platforms (Zervas et al. 2015), the likelihood of exposure increases with the overall number of transactions. This will, over time, make users realize that there is no reliable correlation between photos and behavior. We hence expect that the positive trusting effect based on profile photos will decrease over time.

H_2: *The effect of profile photos on trusting behavior in peer-to-peer sharing transactions decreases over time.*

2.4 Experimental Studies

Despite this evidenced practical relevance of cognitive and affective trust cues, only few studies have experimentally assessed their effects on trusting behavior (Bente et al. 2014a, b; Qiu et al. 2018). Furthermore, the literature review reveals certain, systematic limitations of previous research. First, most of these studies capture either affective *or* cognitive cues, but usually neither both nor–let alone–their interplay. Second, previous studies only consider one side of the trust game without allowing for actual two-way interactions. Third, these studies comprise only one single period of transactions and neglect the dynamic context of most actual trust-building scenarios. Fourth, previous work usually draws on exogenous match-making between transaction partners, which is, of course, highly unrealistic for most peer-to-peer transaction scenarios. Table 1 provides an overview of the most relevant related studies.

3 Method

To test the outlined hypotheses, we conduct a controlled laboratory experiment. Behavioral experiments for investigating platform-related questions have experienced increasing popularity in various fields. Most importantly, the use

Table 1 Related literature (behavioral experiments, incentivized); * = feigned trust game

Source	Experimental design			Trust cue						Trust cue type(s)		Sample	
	Matching	#Periods	Setup	Photo	Avatar	Rating	#Ratings	History	Text	Affect	Cogn	Size	Origin
Bolton et al. (2004)	Exogenous	30	Lab					×			×	144	US
Charness & Dufwenberg (2006)	Exogenous	1	Lab						×		×	n/a	US
Bolton et al. (2008)	Exogenous	15	Lab					×			×	216	n/a
Ben-Ner and Putterma (2009)	Exogenous	7	Lab						×		×	194	US
Bente et al. (2012)	None*	9	Lab	×		×				×	×	36	Germany
Ho (2012)	Exogenous	10	Lab						×		×	58	US
Rezlescu et al. (2012)	None*	40/70/20	Online		×			×		×	×	87	n/a
Rice (2012)	Exogenous	Stochastic	Lab			×					×	90	n/a
Bolton et al. (2013)	By bidding	60	Lab			×	×				×	192	German
Bente et al. (2014a, b) (a)	None*	12	Lab		×	×				×	×	88	Arab/German
Bente et al. (2014a, b) (b)	None*	9	Online		×	×				×	×	126	German
Riedl et al. (2014)	None*	10	Lab	×	×					×		18	German
Teubner et al. (2014)	Endogenous	15	Lab	×	×					×		216	German
Ananthakrishnan et al. (2015)	None*	1	Online						×		×	109	US
Ewing et al. (2015)	None*	5	Lab	×				×		×	×	72	UK
Hawlitschek et al. (2016)	Exogenous	1	Lab							×		92	German
Qiu et al. (2018)	None*	1	Online			×	×				×	5,277	US
Dai et al. (2018)	None*	16	Lab	×		×				×	×	40	US
Ewing et al. (2019)	None*	5	Lab	×						×		143	UK
Ignat et al. (2019)	Exogenous	25	Lab			×					×	30	n/a
Barbosa et al. (2020)	None*	1	Online		×	×						4,499	US/Canadian
Blue et al. (2020)	Exogenous	16	Lab	×		×			×	×	×	27/61/29	Chinese
Kas et al. (2020)	Exogenous	18	Lab					×			×	228	Dutch

Table 1 (continued)

Source	Experimental design			Trust cue						Trust cue type(s)		Sample	
	Matching	#Periods	Setup	Photo	Avatar	Rating	#Ratings	History	Text	Affect	Cogn	Size	Origin
Keser & Späth (2020)	Exogenous	20	Lab			×	×				×	300	German
Teubner & Camacho (2023)	Endogenous	12 (+3)	Lab	×	×					×		216	German
This study	Endogenous	6	Lab	×		×	×			×	×	144	European

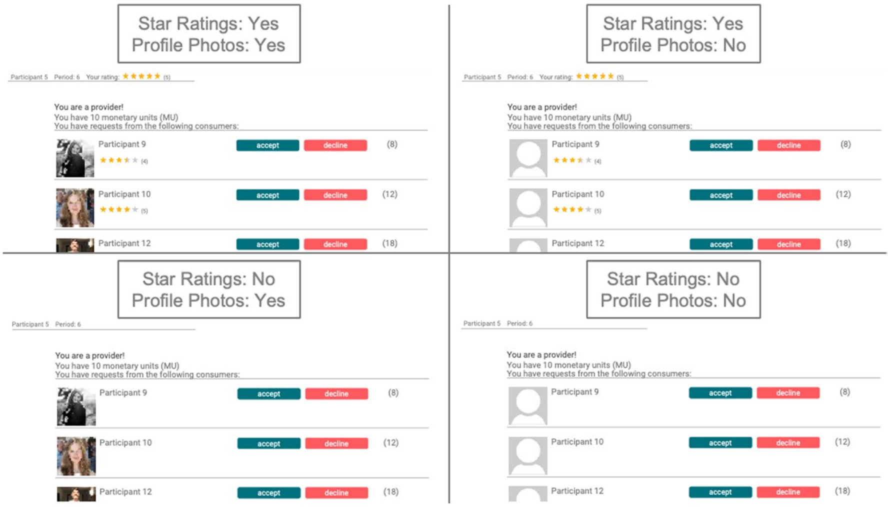


Fig. 1 Examples for the display of user profiles in the four different treatment conditions. *Note*: The examples are from the provider perspective. The corresponding screens for the consumer perspective are shown in Appendix A. Profile photos are pixelated to preserve participants' privacy

of experiments enables causal inferences, augmenting the inferential power of correlative models (Friedman and Cassar 2004). In our experiment, participants engaged in a series of peer-to-peer transactions in a proprietary web interface reflecting typical features of "Airbnb-like" platforms.

3.1 Treatment Structure

The experiment employed a 2 (star ratings: yes/no) × 2 (profile photos: yes/no) full-factorial between-subjects design. Moreover, each participant took either the consumer or the provider role, and kept this role for the entire experiment. Further, to capture the dynamics of cognitive and affective trust cues over time, each experimental session included a total of 6 periods. To avoid end-game effects, some vagueness was introduced in that participants only knew that the experiment would have between 5 and 8 periods (Bolton et al. 2013; Rice 2012).

Illustrating this treatment design, Fig. 1 shows examples of how the user profiles appear in the four treatment conditions. Each session (i.e., cohort) included 12 participants, who were randomly allocated the roles of consumers and providers (6 each) of one and the same treatment condition. Hence, depending on the treatment condition, either all 12 participants in this cohort were able to see and provide star ratings, or none of the participants were. Similarly, either all 12 participants were able to see profile photos, or none of them were. In total, we conducted three sessions for every of the four treatment conditions, resulting in a total sample size of 144 participants (= 4 conditions × 3 sessions/condition × 12 participants/session). This sample size is sufficient to detect main treatment effect sizes of 0.20 with a power of 0.95 (see Appendix C).

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

Profile Photos—In the profile photos conditions, participants' profiles included a photo as provided by the participants themselves. A few days prior to the experiment, we reached out to the signed-in participants via email, notifying them that in the experiment, they would engage with others through a platform-like interface. In this email, participants in the profile photo conditions were informed that they may represent themselves to other participants by means of a profile photo, which they were able to provide via email before the experiment. They were advised that the photo should ideally have a height-width ratio of roughly 4:3 with sufficient resolution. No other instructions were provided with regard to the photo's content or style. While the provision of a photo was voluntary, all 72 participants in the photo condition in fact provided a photo. Within these photos, the participants' face was clearly visible in 60 cases, partly visible in 5 cases, and not visible in 7 cases.[2] In the conditions without profile photos, participants were not able to provide a photo but were represented by a uniform default image (see Fig. 1; right-hand side).

4 Experimental Task

To operationalize and evaluate trusting behavior between peers, we build on Berg et al. (1995)'s trust game. The trust game has become one of the most commonly applied experimental tasks for modeling a large variety of real-world transactions (Riegelsberger et al. 2005). It has been applied to study a variety of artifacts such as avatars (Riedl et al. 2014), ratings (Bolton et al. 2004; Rice 2012), photos (Ewing et al. 2015), and many more.

In the original trust game, two subjects—the trustor and the trustee—engage in a two-staged game. In the first stage, the trustor decides on how much of an initial endowment (e.g., \$10) to transfer to the trustee. The transferred amount y is multiplied by a factor greater than one (e.g., by 3). In the second stage, the trustee then decides on how much of the received (multiplied) amount to return back to the trustor (z). These transferred amounts are generally considered as

[2] Complementary analysis showed that the degree of face visibility within the profile photos did not yield significant differences in behavior (see Appendix B2).

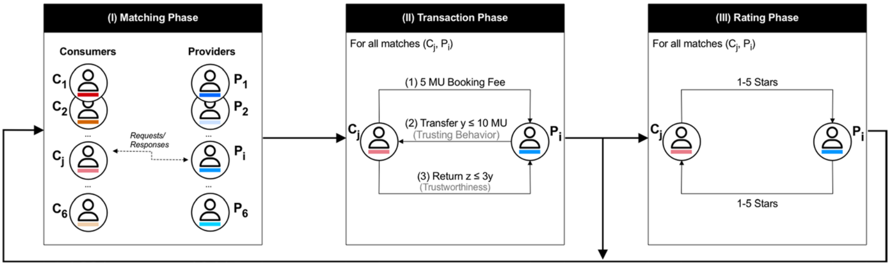


Fig. 2 The three phases of the experimental task. *Note*: As per the treatment structure, each participant engaged in six periods of the experimental task. The rating phase only applies in the star rating condition

manifestations of trusting behavior (y) and trustworthiness (z). Building on the transactions on actual peer-to-peer platforms, we refer to the trust game's players as *providers* (i.e., the trustors) and *consumers* (i.e., the trustees). The basic interaction of the trust game is thus a simplified analogy to the interactions on peer-to-peer platforms, where providers entrust a private resource (e.g., their apartment) to consumers, who will use and return it either in a trustworthy (e.g., clean and intact) or in an untrustworthy (e.g., dirty and/or marred) manner. Further, to model peer-to-peer transactions, we extend the original experiment in two important ways:

1. A **matching phase**, in which participants are able to form dyads themselves, and
2. A **booking fee**, which creates some degree of exposure also for consumers when entering a transaction.

These two extensions refer to the actual booking process on Airbnb-like platforms, where selecting and booking a resource in advance (only based on the available information revealed through the platform) exposes consumers to the risk of paying for a resource that could potentially fail to meet their expectations. Taken together, the experimental task comprised three phases: (I) matching, (II) transaction, and (III) rating, as summarized in Fig. 2. These three phases resemble the basic mechanics of sharing platforms on which consumers first request a resource from a provider and wait for confirmation. Second, after the provider has accepted the request, consumer and provider enter the transaction, where the provider grants access to their resource in exchange for a payment. Third, provider and consumer mutually rate each other based on their transaction experience.

(I) Matching Phase—To capture the notion that peer-to-peer transactions are commonly initiated by consumers and confirmed by providers, we include a matching phase in which participants form dyads themselves (Bolton et al. 2004). Note that any consumer-provider dyad usually only occurs very few times within peer-to-peer sharing (or even only once; Teubner 2018). To account for this fact, consumer

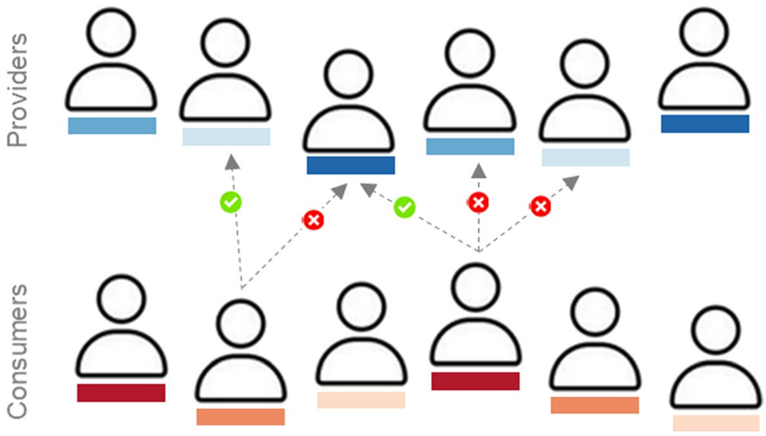


Fig. 3 Exemplary request structure in the Matching Phase

requests are restricted to providers that they had not engaged within the preceding two periods.[3,4] Fig. 3 shows an example of this request mechanics.

The matching phase works as follows: Using the online interface, consumers could send one request to a provider at a time (i.e., asking to enter into a transaction with that provider). If the provider declined the request, the consumer was able to submit a request to the remaining providers. Importantly, in each period, consumers could also abstain from sending requests at all and instead click "skip period". Providers, on the other side, could receive multiple requests from different consumers, but only accept one request per period. Once a request was sent, the provider saw the requesting consumer's profile along with buttons to either accept or decline the request (see Fig. 1). If the provider did not respond to a request within 30 s, the request was automatically rejected. Once a provider accepted a request, all pending requests from other consumers were automatically rejected. Similar to consumers, providers were able to skip the current period and decline (or wait out) all incoming requests.

The matching phase ended when (1) all requests had either been accepted or declined, and (2) no further requests were possible (e.g., because consumers/providers without matches decided to skip the period). Hence, the matching phase represented a two-sided "trade fair," mediated by the online interface in which

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

[4] Due to a technical issue, the restriction on sending requests ruled out only one (rather than two) periods in four of the twelve experimental sessions. This led to the few instances with three-fold transactions. Note that the four affected sessions included all four treatment conditions equally so that no systematic confound was created.

participants negotiated the formation of matches. Participants' photos and/or star ratings (i.e., the main treatment variables) served as cues as to which provider to contact or which consumer's request to accept or reject.

(II) Transaction Phase—Once a provider confirmed a consumer's request, the corresponding consumer-provider dyad entered the transaction phase. This phase includes three steps. In the first step, the consumer pays a booking fee of 5 monetary units (MU) to the provider. This reflects the fact that the consumer faces some exposure in that the provider may not "deliver," that is, for instance, provides an apartment in bad condition. In the experiment, this may occur when the provider decides not to transfer any MUs, which would leave the consumer with a loss compared to not engaging in a transaction at all. In this second step, the provider decides on how much of their endowment to transfer to the consumer (y) where $0 \leq y \leq 10$ MU. Hence, the providers' endowment of 10 MU represents their private asset (e.g., apartment) that they bring into the transaction. The transferred amount y (trusting behavior) is tripled and credited to the consumer. Contextualized to the setting of peer-to-peer platforms, this transfer captures the service delivery from the provider to the consumer. In the third step, the consumer decides on how much to return back to the provider where this values z is an ex-post proxy of the consumer's trustworthiness ($0 \leq z \leq 3y$ MU). It reflects the consumer's behavior or the way the provider's asset is treated (e.g., tidy or devastated apartment). For any transfer $y > 0$, the provider hence faces exposure. The second and third steps of the transaction phase are identical to the original trust game (Berg et al. 1995). A summary screen completes the transaction phase.

(III) Rating Phase—After completing the transaction phase, each consumer-provider dyad enters a rating phase in which they evaluate each other using a star rating score from 1 to 5 stars. Naturally, this phase does only exist in the star rating treatment conditions.

4.1 Overview of Variables

Table 2 provides an overview of the independent variables (treatment structure) and dependent variables (outcome measures).

4.2 Procedure, Sample, and Randomization Check

The experiment was conducted at the experimental lab of a large European university. We recruited 144 participants (56 female, 88 male, average age = 22.2 years, age range = 18 to 36 years) from a student subject pool using the hroot system (Bock et al. 2014). Informed consent was obtained from all participants, explicitly including permission to use the provided profile photos for scientific purposes. The experiment was implemented through a proprietary online environment based on standard web development languages (HTML, PHP, CSS). Written instructions were handed out to all participants and were read out aloud at the beginning of each session.

Participants answered 6 quiz questions to ensure comprehension. All instruction materials are provided in Appendix A. Sessions took about 50 min on average. All monetary units earned within the experiment were converted into EUR (€) at a rate of 4 MU = €1.00. At the end of each session, 3 out of the 6 periods were selected for each subject at random and paid out in cash (average payoff: €11.17).

Table 3 provides sample demographics for each treatment. A set of regression analyses confirms that none of these variables (age, gender, and experience with peer-to-peer platforms–either as a host or as a guest) exhibits significant differences across treatments (Appendix D).

5 Results

Our experimental design yield a multi-level structure of the data, where period is nested within participants (6 periods each) and participants are nested in sessions. As we focus on trusting behavior here, only 6 of the 12 participants per session are relevant (i.e., the hosts). This yields a theoretical maximum of 12 sessions × 6 participants/session × 6 periods/participant × 1 observation/period = 432 observations. As not all participants actually ended up in a transaction in all periods, the de facto number of observations is somewhat lower (n = 394). To analyze the data, we hence use mixed effects regression analysis (lmer in R), estimating fixed effects for our main treatment variables (i.e., photo, rating) as well as period, and random intercepts for subjects and sessions (where subjects are nested within sessions).

Figures 4 and 5 illustrate the overall treatment effects (Fig. 4) as well as how they develop over time (Fig. 5). As suggested there, both star ratings and profile photos have positive effects on trusting behavior, while there does not seem to occur any strong interaction. In all treatment conditions, we observe increases in trusting behavior over time, whereas the profile photo conditions exhibit a markedly different (i.e., curvilinear) pattern where trusting behavior *decreases* after a distinct initial increase.

To corroborate this visual assessment statistically, we consider a set of mixed effects panel regressions (Table 4). In the first two models (I and II), we model linear (and independent) period effects and control for demographic variables (i.e., age, gender, experience). This shows significant general treatment effects both of star ratings ($\beta = 1.338$, $p = 0.011$) and profile photos ($\beta = 1.529$, $p = 0.006$), as well as a positive overall period effect ($\beta = 0.190$, $p < 0.001$). Beyond that, Model II shows that the period effect is predominantly driven by the star rating conditions, which appear to "build up" their effect over time (supporting H1: $\beta = 0.226$, $p = 0.012$) but have no significant effect in the first period yet ($\beta = 0.827$, $p = 0.158$). Conversely, profile photos have an immediate effect right from the start ($\beta = 1.520$, $p = 0.011$), which then, however, is time-invariant. Hence, H2 is not supported ($\beta = 0.002$, $p = 0.984$)—at least when assuming a linear trend. Additionally (not shown in the table here), we did not find any significant interaction between the main treatment variables (photos and ratings; $\beta = -0.956$, $p = 0.375$).

Table 2 Summary of independent and dependent variables in the experiment

Category	Variable	Description	Value scale/range
Independent Variables (Treatment Structure)	**Treatment:** Star Ratings (Cognitive Trust Cue)	Binary treatment variable. In the *star rating condition*, participants evaluate each other in the rating phase (1 to 5 stars). In the *no star rating condition*, participants neither see a star rating nor do they rate their transaction partners	{1 = star ratings, 0 = no star ratings}
	Treatment: Profile Photos (Affective Trust Cue)	Binary treatment variable. In the *profile photo condition*, participants see a profile photo of the other participants. In the *no profile photo conditions*, participants were represented by a default image	{1 = profile photos, 0 = no profile photos}
	Period	Each participant engages in six periods of the experimental task. This allows discerning the dynamic interplay of cognitive and affective trust cues	{1, 2, …, 6}
Dependent Variables (Outcome Measures)	Provider's Trusting Behavior	The *fraction* $y/10$ of the endowment the provider transfers to the consumer ($y \geq 10$ MU). This variable is a measure for the provider's trusting behavior	[0, 1]
	Number of Ratings	The number of ratings a consumer or provider has received. This measure only exists in the star rating condition	{0, 1, …, 5}
	Rating	The rating a consumer (/provider) has provided to evaluate a provider (/consumer) in the rating phase of the experimental task ("stars"). This measure only exists in the star rating condition	{1, 2, …, 5}
	Average Star Rating Score	A consumer's or provider's average star rating score (rounded to the half unit). This measure only exists in the star rating condition	{1.0, 1.5, …, 5.0}
	Consumer's Trustworthiness	The *fraction* $z = return/3y$ of the available amount that the consumer transfers back to the provider ($return \leq 3y$ MU; step 3 of the transaction phase). The return is a measure for the consumer's trustworthiness	[0, 1]

Table 2 (continued)

Category	Variable	Description	Value scale/range
	Provider's Value π_{it}	$\pi = 5 + 10 + y \cdot (3z - 1)$. The value (or payoff) a provider receives, after having transacted with a consumer. This value is determined by the received booking fee (5), the provider's endowment (10), their transfer to the consumer (y), and the relative return from the consumer (z). Note that when no transaction occurs, this payoff is 10 (endowment)	[5, 35]

Table 3 Sample statistics on demographic control variables by treatment

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

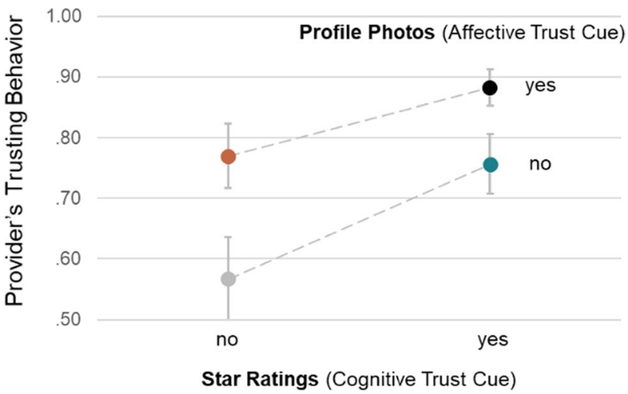


Fig. 4 Main treatment effects of trust cues on provider's trusting behavior. Note: Error bars indicate 95% confidence intervals

As suggested by Fig. 5, the assumption of linearity, however, does not hold as there appears to exist a curvilinear progression when profile photos are present. In Models III a-d, we hence introduce quadratic period effects. To avoid uninterpretable triple interactions (Photos × Ratings × (Period + Period^2)), we estimate a separate model for each treatment condition. These analyses show that both conditions with profile photos exhibit a curvilinear structure with positive and significant linear estimates ($\beta = 1.739$, $p < 0.001$; resp. $\beta = 0.850$, $p < 0.001$) and negative and significant second-order estimates ($\beta = -0.322$, $p < 0.001$; resp. $\beta = -0.19$, $p < 0.01$). When only star ratings are present, there is a "simple" linear and positive time-trend ($\beta = 0.582$, $p < 0.001$). In the setting with neither profile photos nor star ratings, no significant period effect occurs, albeit the direction is slightly positive ($\beta = 0.411$, $p > 0.05$).

None of the control variables (gender, age, experience) exerts significant effects on trusting behavior in any of the models.

5.1 Effect Decomposition of Star Ratings

In line with previous research, we have established the link between the presence of a star rating system and trusting behavior and seen an intricate dynamic pattern.

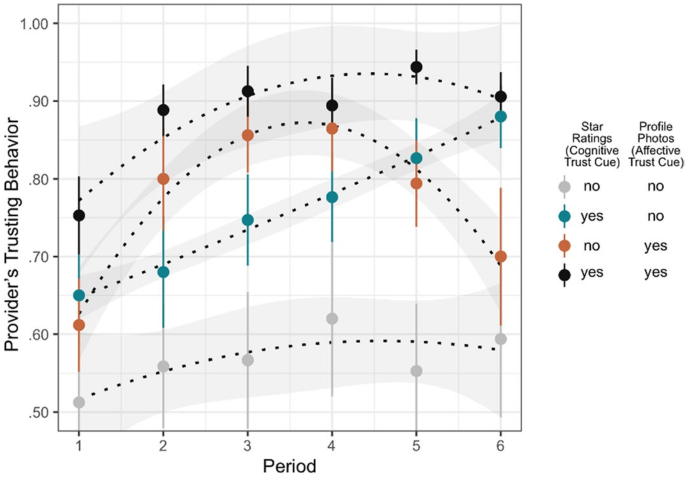


Fig. 5 Course of provider's trusting behavior across periods. Note: Error bars indicate 95% confidence intervals

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

Hence, it is important to delineate these effect components in order to assess which fractions of the observed trusting behavior are actually due to the displayed rating scores (i.e., their net effect). As a next step, we hence drill down how trusting behavior evolves over the course of the six periods. Note that providers exhibit substantial trusting behavior even in the treatment condition in which no trust cues whatsoever are displayed ("baseline" condition). In fact, in this condition, providers transfer about half of their endowment (51.3%) to consumers on average. Moreover, there exists a slightly increasing trend. We hence consider these the General Trust Baseline and the General Time Effect (see Table 5 and Fig. 6). Also, note that in the very first period, participants in the star rating conditions were not able to draw on specific rating scores because no participant had had the chance to collect ratings at that point. Nevertheless, we still observe higher first-period trusting behavior as compared to participants in the non-star-rating conditions. This *shadow-of-the-future* effect indicates that the mere existence of the star rating system (even without the display of actual rating scores) facilitates trusting behavior due to the anticipation of rating and being rated as outlined above. Making use of this temporal distinction, we can further subtract the shadow-of-the-future effect in all subsequent

Table 4 Regression models (DV = Provider's Trusting Behavior)

			None	Ratings only	Photos only	Both
	I	II	III(a)	III(b)	III(c)	III(d)
(Intercept)	3.179 (1.968)	3.481 (1.974)	0.830 (7.818)	6.607 (4.301)	2.384 (3.847)	**7.911 (2.243)****
Star Rating	**1.388 (.540)***	0.827 (.584)	–	–	–	–
Profile Photo	**1.529 (.548)****	**1.520 (.592)***	–	–	–	–
Period (0–5)	**0.190 (.045)*****	0.076 (.078)	0.411 (.406)	**0.572 (.190)*****	**1.739 (.375)*****	
Period ^ 2	–	–	−0.079 (.078)	−0.044 (.037)	**−0.322 (.072)*****	**−0.119 (.036)****
Rating × Period	–	**0.226 (.089)***	–	–	–	–
Photo × Period	–	0.002 (.089)	–	–	–	–
Provider Is Female	−0.553 (.566)	−0.555 (.566)	−1.760 (1.630)	0.139 (1.182)	−0.115 (1.035)	0.157 (.733)
Provider's Age	0.090 (.087)	0.089 (.087)	0.208 (.343)	−0.060 (.197)	0.167 (.175)	0.011 (.087)
Provider's Experience	0.688 (.594)	0.684 (.594)	0.935 (1.712)	2.024 (1.163)	0.373 (1.236)	−0.614 (.793)
Random effects						
σ^2	2.31	2.28	3.39	0.84	3.22	0.81
$\tau_{00\ \text{prov:session}}$	4.72	4.73	10.53	4.86	3.84	1.60
$\tau_{00\ \text{session}}$	0.00	0.00	0.02	0.00	0.00	0.00
ICC	0.67	0.68	0.76	–	0.54	–
N_{provider}	72	72	18	18	18	18
N_{session}	12	12	3	3	3	3
Observations	394	394	96	97	100	101
Marginal R^2 / Conditional R^2	0.186/0.733	0.190/0.737	0.070/0.774	0.615/–	0.124 / 0.601	0.310/–

Mixed effects models with random effects for subjects nested in sessions. DV = dependent variable; standard errors in parentheses; *** $p < .001$; ** $p < .01$; * $p < .05$

Table 5 Delineation of star rating's effect on trusting behavior

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

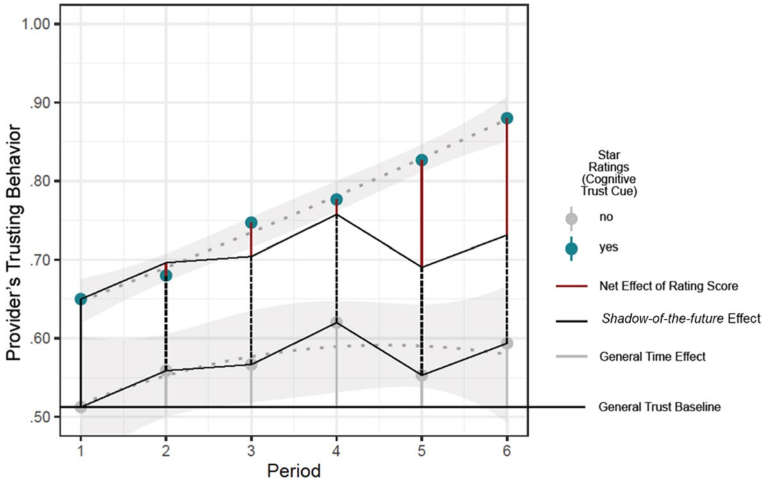


Fig. 6 General Trust Baseline and resulting *shadow-of-the-future* effect, Net Effect of Rating Score, and General Time Effect across periods

periods (t ≥ 2), yielding a residual (red lines in Fig. 6). This residual can be considered as the Rating Score Net Effect. We observe that the net effect increases only slowly within the first four periods and then jumps to a level of about 0.15, comparable in size to the shadow-of-the-future effect. This observation suggests that the impact of time (and/or the number of underlying ratings) on the net effect of an aggregated star rating score is more complex than a simple linear trend, potentially involving discontinuities.

5.2 Complementary Analyses

Star Ratings and Trusting Behavior (Appendix B1): Overall, our results' rating distributions are consistent with what is typically observed on platforms. Moreover, the analysis reveals that the ratings providers and consumers receive depend on their respective behavior (i.e., the amount they transfer or transfer back). Importantly, also consumers' chances of being accepted as well as providers' trusting behavior depend on the consumer's aggregated star rating score. Hence, behavior is reflected in star ratings and, vice versa, star ratings affect behavior.

Visual Photo Properties and Trusting Behavior (Appendix B2): Similar to the analysis of specific star rating scores, we consider how specific visual properties of the profile photos, such as face visibility, attractiveness, and visual trustworthiness, affected trusting behavior. However, we did not find any evidence for significant effects with regard to these attributes.

Value Decomposition (Appendix B3): Combining the findings of trusting behavior (providers' behavior) and ex post trustworthiness (consumers' behavior), we can decompose the overall value providers receive along these (factorial) partial effects. This analysis grants further insight into how specifically the trust cues "generate" value. For instance, we find that while overall, trusting behavior is similar when either one or the other cue type is present, the presence of star ratings yields higher trustworthiness. This treatment difference can hence be attributed to the ratings' effect on consumers rather than provider behavior.

Matches and Requests (Appendix B4): Both across treatments and periods, we observe non-significant differences with regard to the number of transactions. The matching rate exceeds 90% throughout the experiment, so that basically every participant is matched in almost every period. However, both star ratings and profile photos have positive effects on the share of participants who sent at least one request. However, as there are no significant effects on the fractions of participants who received at least one request, the additional requests cannot be distributed evenly but concentrate on those who already receive requests from other participants. Consequently, this does not result in differences in the number of matches. Period did neither affect the number of matches or request behavior.

6 Discussion

The number of peer-to-peer sharing businesses is growing and already shapes a substantial part of the e-commerce landscape (Gawer 2014; Mittendorf et al. 2019; Möhlmann 2021). At the same time, creating trust among users is of the utmost importance for these platforms, particularly for new users (Hesse et al. 2022).

6.1 Cognitive Trust Cues Over Time: Effect of Star Ratings

In the very first period of our experiment, participants in the star rating conditions were not yet able to draw on any insights communicated by rating scores (as they were still in the process of building their reputation capital). Still, in these conditions, we observe more pronounced trusting behavior (i.e., higher transfers) as compared to the non-star-rating conditions. This finding reflects previous research such as by Rice (2012), who distinguishes between the trust-building effect of the mere existence of a rating system and specific scores. Our findings indicate that already the existence of a rating system per se affects trusting behavior. We offer a potential explanation for this observation based on participants' *anticipation* of being rated—the shadow-of-the-future effect. In a sense, the prospect of leaving a rating and being rated seems to represent a mutually impending threat, causing participants to exhibit trusting as well as trustworthy behavior. Next, the effect of star ratings on trusting behavior becomes stronger over time. The fact that star ratings seem to represent a reliable cue, and that their effect is steadily increasing for increasing numbers of underlying ratings, is consistent with previous research (Burtch et al. 2014; Cabral ansd Hortaçsu 2010).

6.2 Affective Trust Cues Over Time: Effect of Profile Photos

Interestingly, we find that that the effectiveness of profile photos for engendering trust follows an inverted u-shape over time. Profile photos start out to function as a relevant trust cue, and this effectiveness then increases even further. However, its trust-promoting capability collapses back to approximately its origin level later on. The fact that this pattern can be observed in both photo conditions (i.e., with and without star ratings) is not only an indicator for the reliability of this result but also highlights the importance of viewing it from a dynamic (rather than from a static) perspective. We suggest that the eventual decrease of trusting behavior is driven by the drop in returns, which occurs in the middle of the experiment at the peak of the trusting behavior curve (see Fig. 29, Appendix B1). This drop precedes the downward slope in the inverted u-shape curve. This drop can be interpreted from two perspectives: First, it implies emerging exploitation of providers' trusting behavior by consumers. This exploitation can be interpreted as a counterargument that burdens the positive effect of the affective trust cue. Second, Petty and Cacioppo (1986) describe an "elaboration continuum," which states that the mode of information evaluation is not subject to a strictly binary classification but rather a continuous scale. As such, the mode of processing the affective cue may shift across transactions.

Conceivably, overall trusting behavior may be subject to two partial effects: (1) the accumulation of experience or confidence within the transactional environment, and (2) the demonstrated effectiveness of cues. Initially, participants have limited or no experience/confidence within the transactional environment, including familiarity with the cues or the overall experimental setup. This initial lack of experience may lead them to adopt a rather cautious approach, resulting in limited trusting behavior, reflected in low transfers. Providers who are unsure whether the trust they put in their respective transaction partner will ultimately be rewarded or exploited, therefore, may behave rather cautiously in their first transactions. Simultaneously, participants may initially have rather high expectations concerning the cues' effectiveness or their informational value. Initially, expectations should be high as providers see potential transaction *showing their colors,* that is, revealing their identity and thus personally vouching for their trustworthiness. However, over time, these expectations may undergo certain transformations. As participants engage in multiple transactions over time, they continuously realize that profile photos may not align with those initial (high) expectations. For instance, hosts are likely to–eventually–experience disappointing results, such as by receiving low or zero returns. The more often such exploitative behavior is experienced, the lower the expectation towards the photo cue should become.

It can be argued that, in order to function as a trust-building device, users need to be both (1) experienced with the decision environment in which they encounter profile photos and (2) have faith in the photos' effectiveness. Hence, trusting behavior emerges as the *interaction* of both (see Fig. 7). Given that one factor (experience) increases over time and the other factor (faith in effectiveness) decreased (e.g., towards some level close to zero), the result is a curvilinear progression of trusting behavior (inverted u-shape).

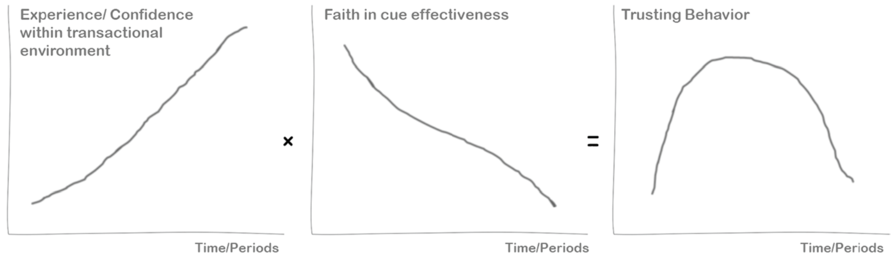


Fig. 7 Conjectured emergence of trusting behavior as the interaction of experience (increasing over time) and faith in cue effectiveness (decreasing over time)

Of course, this is merely a speculative explanation at this point, but it offers a rationale for the observed behavior. Future research will have to examine the particular levels and courses of experience and faith in effectiveness as well as their interaction and effects on trusting behavior.

Overall, the finding of the inverted u-shape suggests that profile photos convey varying effects on trust, depending on the specific phase of transactions. Thus, our results extend previous research, which has often abstracted from such potential time-dependencies of interpersonal trust by taking a snap-short perspective rather than presenting sound empirical findings how trust behavior may change over time (Bapna et al. 2017; Gefen 2000; Gefen et al. 2003; Pavlou and Gefen 2004).

6.3 Dynamic Complementarity of Cognitive and Affective Trust Cues

To some extent, our findings reveal that cognitive and affective trust cues complement each other over time. In contrast to star ratings, profile photos allow a "kick-starting" of trust in early phases in which star ratings are less accurate and reliable, helping to overcome this cue's inherent "cold-start problem" (Hesse et al. 2022; Wessel et al. 2017). However, the presence of both trust cues leads to higher trusting behavior than when only one is available. Interestingly, the cues do not significantly interact and have an additive effect. This can be interpreted as support for the assumption that the cues are processed through different mental paths. In fact, Petty and Cacioppo (1986) already pictured this additivity when combining centrally and peripherally processed information for one-time exposure–a presumption that seems to hold and extend to exposure throughout multiple periods when applied in the context of trust behavior across repeated rounds of interaction.

6.4 Theoretical Contributions

Our study makes several contributions to trust research in the context of online sharing platforms (Gawer 2014; Lucas et al. 2021; Möhlmann 2021). Previous research widely agrees that the effects of trust cues on trusting behavior are relatively stable across different phases of their "lifecycle" as their effects are time-invariant. To this end, McKnight and colleagues have theorized that certain trust cues may indicate stability through structural assurances and situational normality (McKnight et al.

1998, 2002a). Only recently, the issue of longitudinal examination of trust cues has begun to receive increased attention (van der Werff and Buckley 2017). Yet, previous research does not sufficiently capture on how the trust-building capacity of cognitive and affective trust cues on trusting behavior may be subject to dynamic changes across multiple periods and/or transactions. We extend previous research addressing cognitive and affective trust cues by taking a "dynamic" perspective. We do so by drawing on assumptions about the central and peripheral route of information processing as introduced in the ELM (Petty and Cacioppo 1986; Petty et al. 1983). In line with our theoretical reasoning, assumptions about stable or increasing effects of trust cues apply to star ratings (cognitive trust cues), associated with the central route of information processing but not to profile photos (affective trust cues), associated with the peripheral route. Rather than assessing their trust-building potential in isolation (Komiak and Benbasat 2006; Stewart and Gosain 2006), we analyze the combination and interplay of two specific types of cues. Thereby, we follow the calls for more research on "the roles of [information] repetition and [information] variation" and that "researchers and practitioners would benefit from a better understanding of the degree to which the attitudes created or changed by their efforts persist over time, resist change, or predict behavior" (Schumann et al. 2012, p. 62). To investigate trust-building through the respective trust cues as a dynamic process, we conducted an experimental study with multiple transactions. Showing that cognitive and affective trust cues exhibit time-dynamic complementarity, our findings indicate that previous research may have underestimated the role of affective trust cues so far as they play an important role in complementing cognitive cues–in particular in the earlier stages of the usage process.

6.5 Methodological Contributions

Our study offers a distinct methodological contribution. Specifically, we extend the trust game (Berg et al. 1995) to the context of online sharing platforms, by providing a controlled experimental setting in which the emergence of trust behavior can be investigated over the course of multiple periods. Complementary to the existing approaches drawing on surveys (Dann et al. 2020; Ert et al. 2016; Teubner et al. 2022), experiments (Teubner 2022; Teubner and Camacho 2023), or field data (Edelman et al. 2017; Fradkin et al. 2018), this experimental setup provides a proxy for understanding user behavior on peer-to-peer sharing platforms, particularly when considering how trusting behavior evolves dynamically over time. Our experimental design complements previous research by allowing for a more natural investigation of transactional behavior. In contrast to prior studies, we use a "natural" endogenous process of matchmaking with requests and responses, similar to what is observed on many (if not most) actual peer-to-peer online platforms.

6.6 Managerial Implications

Our findings have important implications for consumers, providers, and managers of online sharing platforms. Specifically, they show that these stakeholders should be aware of the different phases and how they may affect trusting behavior (Lucas et al. 2021; Möhlmann 2021). On the one hand, platform managers should actively and early on encourage consumers and providers to upload profile photos as a means to kick-start the formation of trust–particularly during the initial and early stages of platform evolution. On the other hand, it is important for platform managers to understand that the beneficial effect of profile photos decays over time. Hence, a rating-based system should be used and users should be prompted to make active use of it. It also emphasizes the dual role of human information processing via central and peripheral routes, both of which should be reflected in platform design (Cyr et al. 2018). While we focused on a scenario with an open, market-based request-and-response process (endogenous matching) and highly transactional exchanges, there is reason to believe that our results may provide insights for a broader range of online platforms. While on platforms such as Airbnb, most users upload profile photos and evaluate each other after most transactions, there exist other platforms such as Craigslist or Gumtree (some of the most popular peer-to-peer platforms in the US, the UK, and Australia) that do not enable and/or encourage their users to do so (Hesse et al. 2020). Our findings suggest that platforms should reconsider their practices. Furthermore, on some platforms, even if they allow users to upload personal photos, this option is far from being used by everyone (Hesse et al. 2020). Uber seems to have even experimented with "forcing" users to leave a rating, for instance, by requiring them to provide feedback about a driver's performance before allowing them to engage in another transaction.

6.7 Limitations and Future Work

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

Behavior as a Proxy of Trust: The operationalization of trusting behavior as the amount providers are willing to transfer represents a limitation–as are any behavioral proxies for trust (such as the trust game). While this approach certainly captures *one* aspect of trust, it is an incomplete reflection as behavior is a multifaceted concept influenced not only by trust, but also by other factors such as risk aversion, prior experience, or necessity.

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

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

Dynamic Effects of Other Trust Cues: Our study provides a sound understanding of the effects of star ratings and profile photos, common examples of cognitive and affective trust cues, over time. It is important to note that we addressed that most prototypical trust cues capturing cognitive and affective characteristics, while other trust cues may in theory comprise elements of both. Thus, future research should consider to investigate the effects of other trust cues (e.g., labels, badges, certificates, text elements, videos). From the perspective of an online platform provider, it is essential to leverage a portfolio of trust cues, which add up to an overall trust enhancing effect that is effective over the whole platform evolution.

6.8 Concluding Note

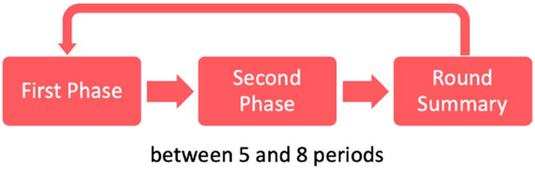
Both cognitive (e.g., star ratings) and affective (e.g., profile photos) trust cues represent effective means for trust-building. While we find no evidence for an interaction of these cues, they complement each other over time. Our findings inform both platform operators and users attempting to support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

Appendix A: Experiment Instructions

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

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

Fig. 8 Experiment overview



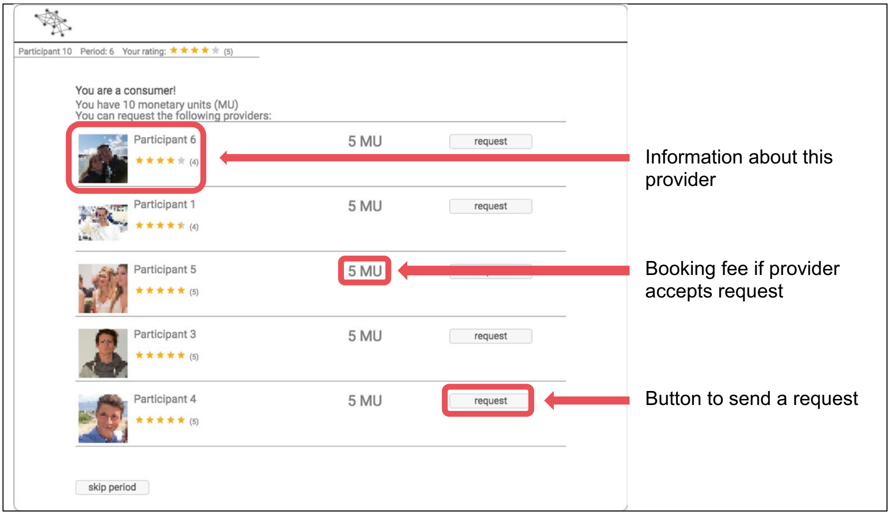


Fig. 9 List of providers

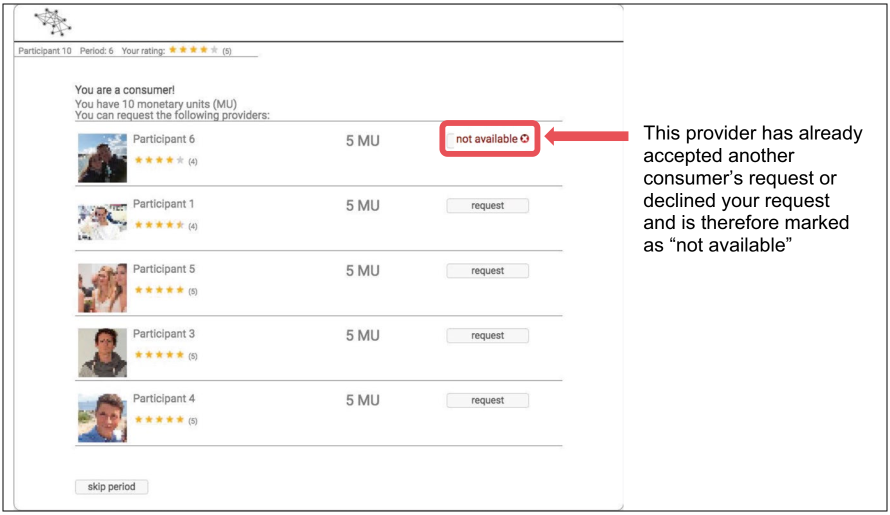


Fig. 10 Not available provider

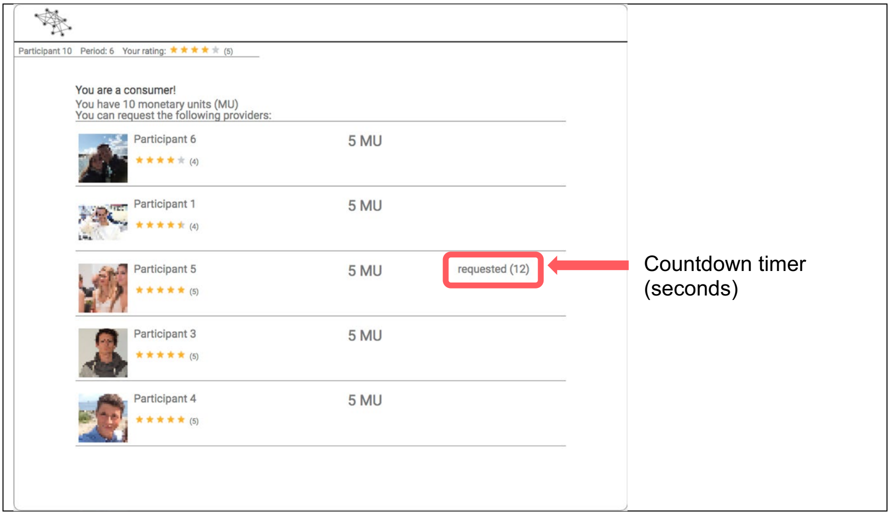


Fig. 11 Request countdown

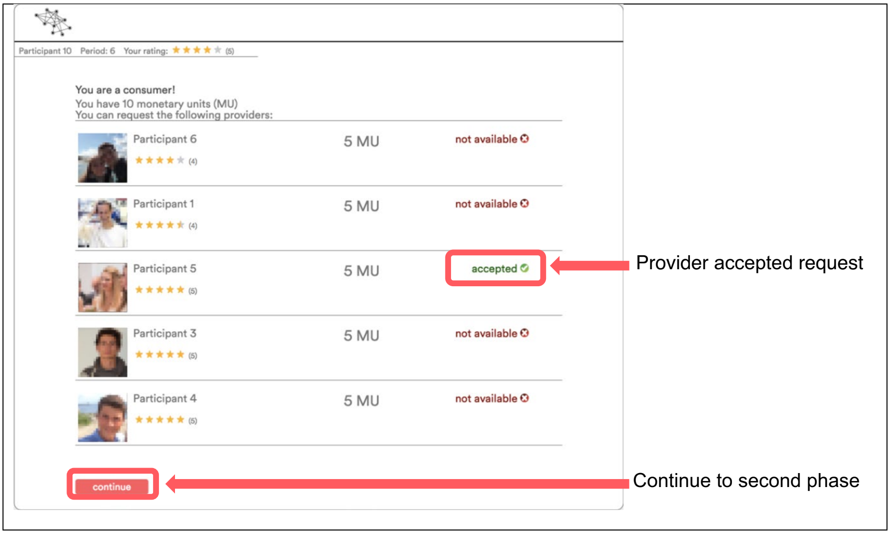


Fig. 12 Accepted request

entire experiment (Figs. 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26 and 27).

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

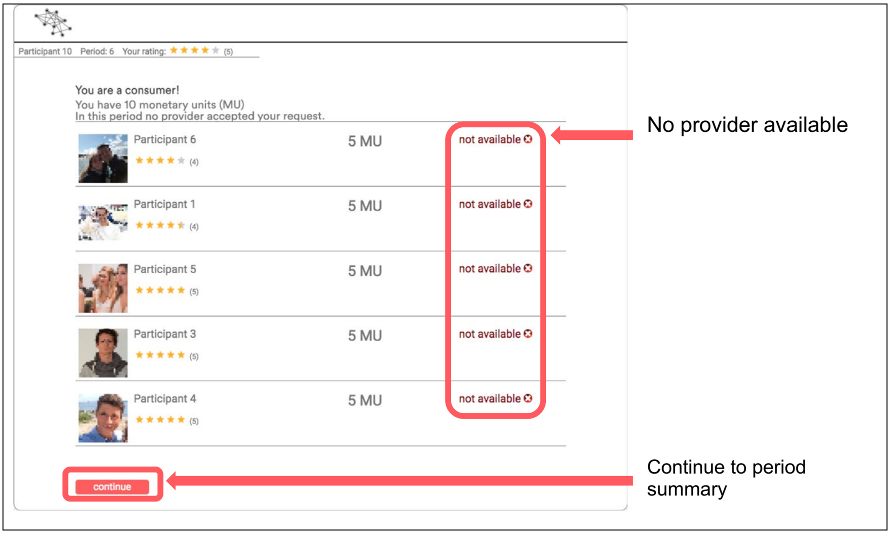


Fig. 13 No provider available

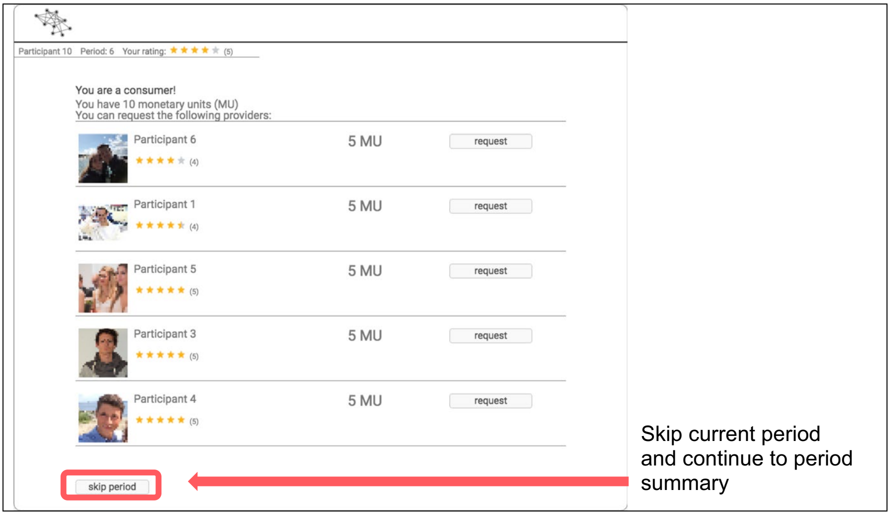


Fig. 14 Skip current period

the experiment, three of your periods are randomly selected and you get the payoffs from those periods paid out.

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

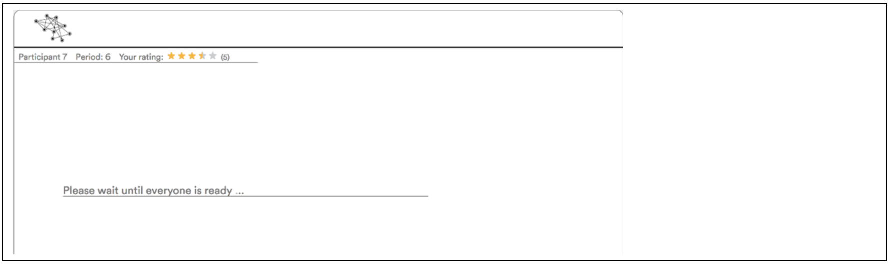


Fig. 15 Waiting screen

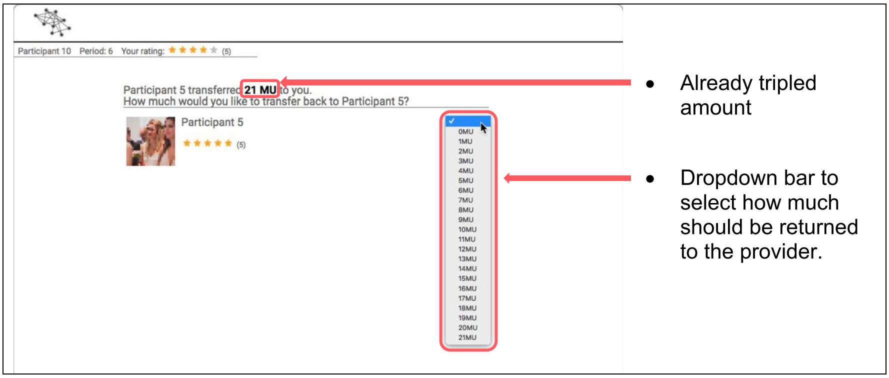


Fig. 16 Return to provider

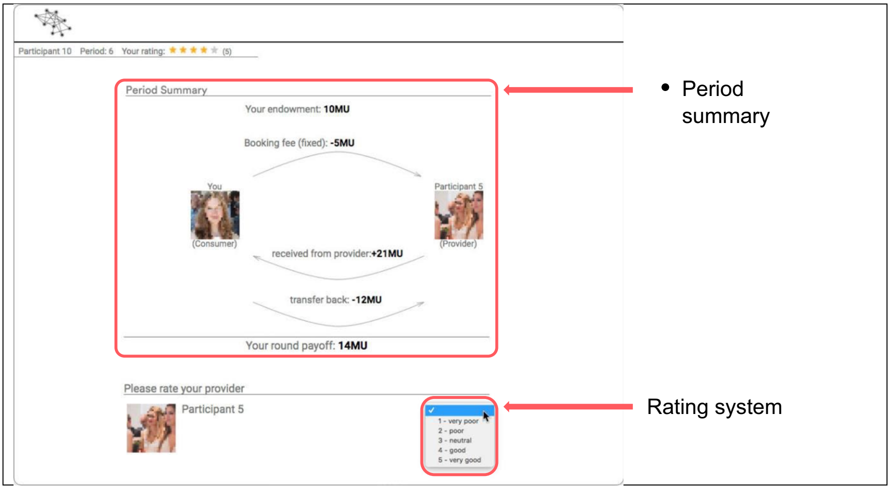


Fig. 17 Period summary (consumer)

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

Fig. 18 Comprehension questions (consumer)

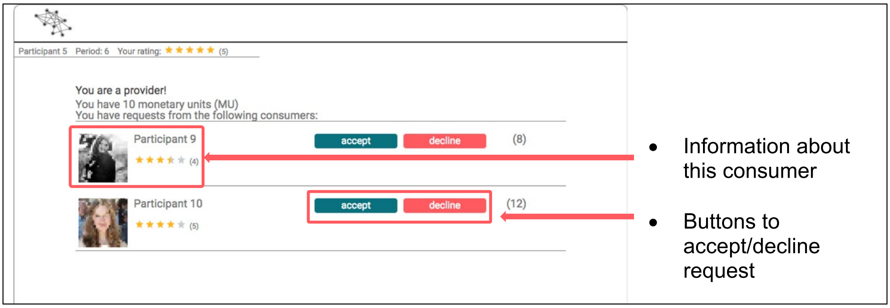


Fig. 19 Available consumer requests

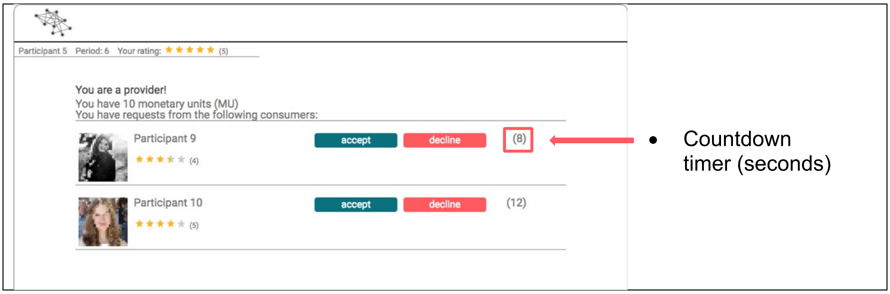


Fig. 20 Request countdown

list with information about all providers including the applicable booking fee if a provider accepts your request.

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

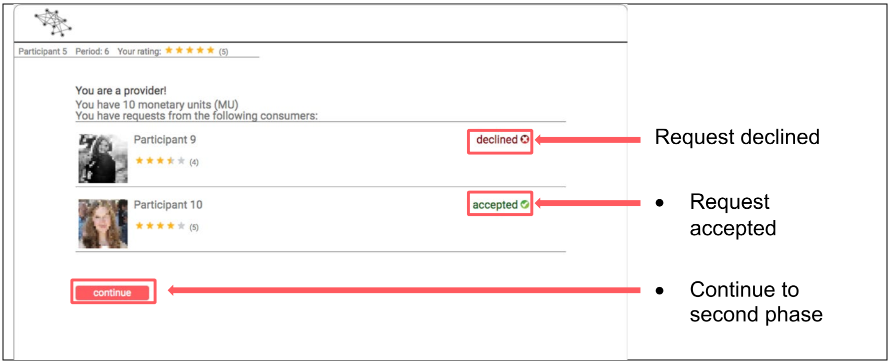


Fig. 21 Accepted request

Fig. 22 No consumer requests

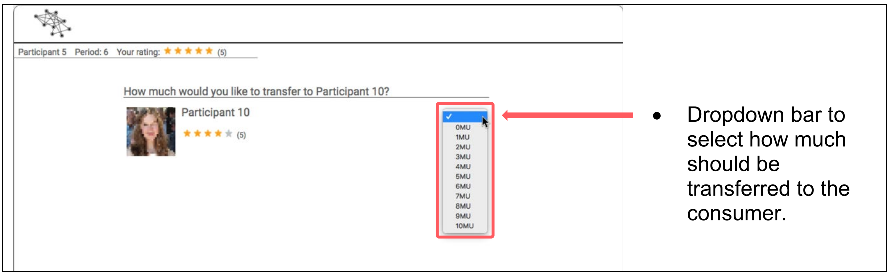


Fig. 23 Transfer to consumer

Requests are valid for 30 s. The remaining time is shown by a countdown. During this time, you cannot send any further requests to other providers. Non-processed requests (in this time) will be automatically withdrawn.

As soon as a provider has accepted your request, a confirmation notification will appear on your screen. The 5 MU booking fee will be subtracted from your

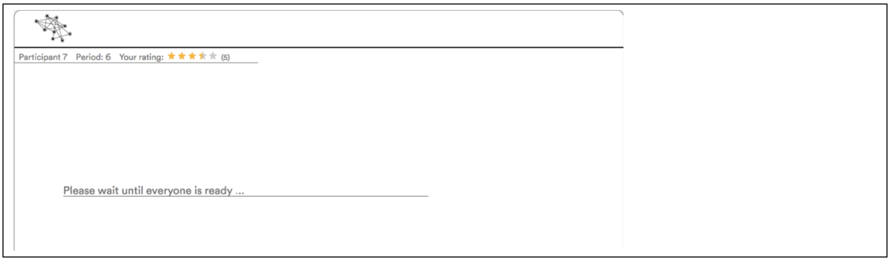


Fig. 24 Waiting screen

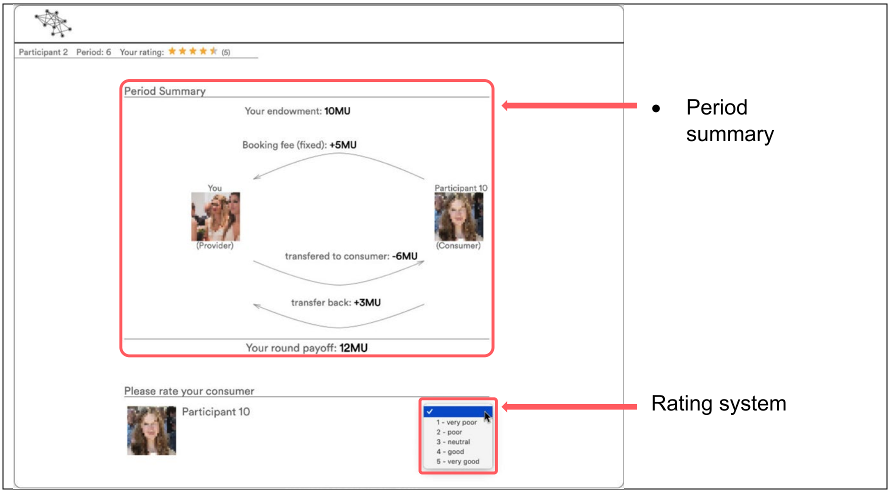


Fig. 25 Period summary (provider)

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

Fig. 26 Comprehension questions (provider)

endowment and transferred to the provider. Clicking the "continue" button brings you to the second phase of the current period.

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

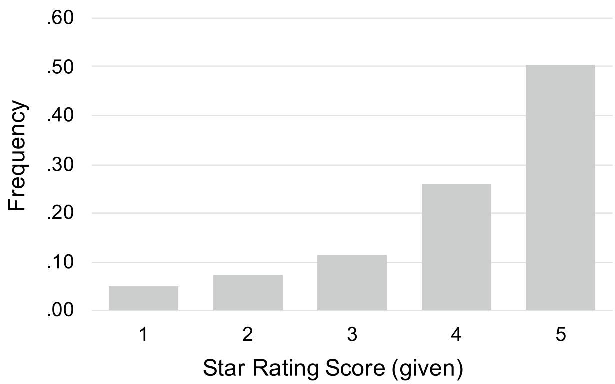


Fig. 27 Rating distribution (based on 396 star ratings from 198 completed transactions)

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

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

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

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

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

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

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

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

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

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

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

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

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

Appendix B1: Star Ratings and Trusting Behavior

To shed further light on how the availability of star ratings contributes to engendering trust, we consider which star ratings were exchanged, how *specific* scores are associated with trusting behavior, and also how–in turn–behavior is reflected in star ratings. To do so, we focus on the corresponding subset in which star ratings were available. First, it strikes the eye that the distribution of exchanged star rating scores greatly resembles distributions observed on actual peer-to-peer sharing platforms (Fig. 27; mean = 4.09 stars, SD = 1.17) with five stars being the most frequently given score (50% of all cases). In this regard, the experiment's rating distribution is consistent with what is typically observed on contemporary peer-to-peer platforms and review sites.

Second, as shown in Fig. 28, providers' trusting behavior (as per the transferred amount) is strongly correlated with the star rating they receive from the consumer (Pearson's $r = .686$, $p < .001$). Moreover, consumers' trustworthiness (as per the returned amount) is strongly correlated with the star rating *they* receive from the provider ($r = .731$, $p < .001$). Thus, within the scope of our experiment, star rating scores did, in fact, reflect (past) behavior and hence carried informational value (*star ratings as the result of behavior*).

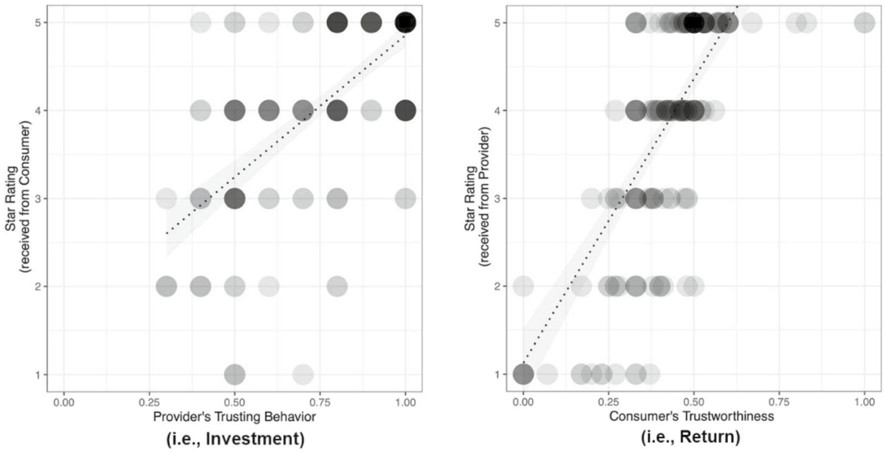


Fig. 28 Correlation of provider's trusting behaviour (i.e., investment), consumer's trustworthiness (i.e., return), and the associated star ratings received from the respective other party

Table 6 Regression models for request acceptance and trusting behavior

	DV = Provider Accepts Request (yes = 1, no = 0)	DV = Provider's Trusting Behavior [0, 1]
Consumer's average rating score $^{(1–5)}$	**1.283*****	**0.072*****
	(.259)	(.012)
Treatment: Profile Photos $^{(yes=1)}$	0.021	**0.128**
	(.324)	(.051)*
Period $^{(2–6)}$	**0.196***	**0.027*****
	(.097)	(.004)
Time to Accept/Decline $^{(sec)}$	**0.046****	
	(.016)	
Intercept	**−6.204*****	**.364*****
	(1.236)	(.067)
Observations	298	162
Random Effects		
$_{\sigma}2$	3.29	0.01
τ_{00} subjectID	0.31	0.02
ICC	0.09	0.79
N subjectID	36	36
Marginal R^2/Conditional R^2	0.212 / 0.280	0.223 / 0.840

(General) linear mixed effect regressions for whether or not provider accepts request and provider's trusting behavior (subject random intercepts). DV = dependent variable; standard errors in parentheses; *** $p < .001$; ** $p < .01$; * $p < .05$

Third, we consider how the information carried in the average star rating scores translated into behavior, that is, *behavior as a result of star ratings*. To do so, we first consider whether consumers' *chances of being accepted* depended on their aggregated rating score. Moreover, once a transaction was initialized, we consider the *provider's trusting behavior* based on the consumer's current average star rating. Note that overall, 61% of all 645 sent requests were accepted. Thus, a considerable fraction of requests were actually declined, which is consistent with results from the platform literature. Table 6 summarizes regression estimates for (1) the probability that a provider accepts a consumer's request and

(2) the provider's trusting behavior. We find that higher star rating scores increase consumers' *chances of being accepted* ($\beta = 1.283$, $p < .001$) and *higher levels of trusting behavior* once a transaction was realized ($\beta = .072$, $p < .001$).

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

Appendix B2: Face Visibility, Attractiveness, and Visual Trustworthiness

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

We now consider whether, and if so, how this information translated into behavior, that is, *behavior as a result of specific photo properties.* Table 7 summarizes the logistic and regular regression estimates for (1) the probability that a provider accepts a consumer's request and (2) the provider's trusting behavior (as per the transferred amount to the consumer). The results show that neither face visibility, visual trustworthiness, attractiveness, nor gender significantly affect acceptance or trusting behavior. This suggests that–compared to the paramount effect of profile photo availability as such–specific photo characteristics played a subordinate role.

Table 7 Regression models for request acceptance and trusting behavior

	DV = Provider Aacepts request (yes = 1, no = 0)	DV = Provider's trusting behavior [0, 1]
Consumer Face Visibility (yes = 1)	−0.157	0.086
	(.482)	(.052)
Consumer Attractiveness (1–5)	−0.216	−0.033
	(.282)	(.030)
Consumer Visual Trustworthiness (1–5)	0.339	0.002
	(.310)	(.034)
Consumer Gender (female = 1)	0.068	0.016
	(.268)	(.029)
Treatment: Star Ratings (yes = 1)	−0.220	0.100
	(.239)	(.056)
Period (1–6)	0.031	**0.019****
	(.068)	(.006)
Time to Accept/Decline (sec)	**0.029***	
	(.013)	
Intercept	−0.438	**0.748*****
	(.992)	(.114)
Observations	330	201
Random effects		
σ^2	3.29	0.02
τ_{00} subjectID	0.00	0.02
ICC	–	0.50
N subjectID	36	36
Marginal R^2/Conditional R^2	0.031 / –	0.083 / 0.537

(General) linear mixed effect regressions for whether or not provider accepts request and provider's trusting behavior (subject random intercepts). DV = dependent variable; standard errors in parentheses; *** $p < .001$; ** $p < .01$; * $p < .05$

Appendix B3: Trusting Behavior-Trustworthiness Effect Decomposition

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

$$\pi_{it} = 5 + 10 + y_{it}\left(3z_{jt} - 1\right)$$

where y_{it} denotes the transferred amount (0–10; i.e., proxy for the provider's trusting behavior), z_{jt} is the consumer *j*'s relative return (0–1; i.e., proxy for the consumer's ex-post trustworthiness), and the absolute values of 5 and 10 denote the booking fee

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

Treatments		Provider's trusting behavior	Consumer's trustworthiness	Provider's value π
Star ratings	Profile photos			
		.567	.294	.932
	×	.770	.380	1.11
×		.757	.427	1.21
×	×	.882	.431	1.26

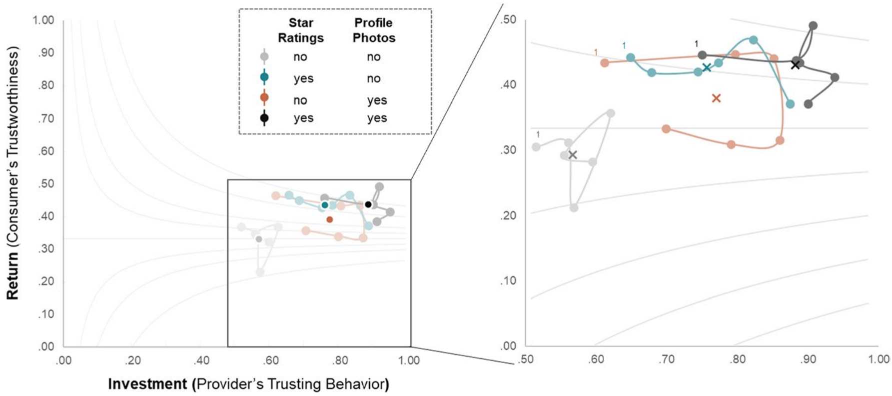


Fig. 29 Effect decomposition for each treatment condition throughout the six periods with iso- value lines. The curve of the photos-only treatment (orange) shows the inverted u-shape (tilted to the side). Note: [1] denotes treatment's first period, × indicates overall average treatment value

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

The baseline treatment exhibits both the lowest overall levels of trusting behavior and returns. Comparing the only-star-ratings with the only-profile-photos treatment shows that while trusting behavior was higher in the profile photos treatment, trustworthiness was higher in the star ratings treatment. Beyond these overall findings, Fig. 29 depicts the course of trusting behavior and trustworthiness across treatments and individual periods, providing more detailed insights into the development of these values. The iso-value lines indicate equal levels of π. Interestingly, for the only- star-ratings treatment, trusting behavior initially rises until the third period, while trustworthiness remains relatively constant. From the fourth period on, however, the return rates decline sharply, which subsequently is followed by lower levels of trusting behavior, causing the aforementioned inverted u- shape.

Table 9 Number of transactions in the respective treatment conditions

		Profile photos	
		No	Yes
Star ratings	No	96	100
	Yes	97	101

Table 10 Distribution of absent requests sent and received across treatments

Star ratings	Profile photos	Possible cases [1]	Cases in which no requests were:	
			Sent	Received
No	No	108	8	10
	Yes	108	1	6
Yes	No	108	0	10
	Yes	108	0	5
Overall		432	9 (2.1%)	31 (7.2%)

[1] Per treatment condition, there were 3 sessions · 6 participants · 6 periods

Considering the ×-marks in Fig. 29 illustrates along which partial effects the treatment conditions (and hence the trust cues) make a difference with regard to value capture by providers. As can be seen, "activating" either one of the cues increases both trusting behavior *and* trustworthiness since both colored marks lie further up and further right than the grey mark. While both of the cues yield similar trusting behavior, star ratings yield higher degrees of trustworthiness. This treatment difference can hence be attributed to the star ratings' effect on consumer rather than provider behavior. Now, considering how the additional value is captured when both cue types are present at the same time, we see that it is mainly the provider's trusting behavior that makes the difference.

Appendix B4: Realization of Matches and Request Behavior

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

Request Behavior: Next, we control for potential confounds regarding requesting behavior. Table 10 shows how the rare cases that, in a given period, a participant did not (1) send at least one request (consumers) or (2) receive at least one request (providers) are distributed across the four treatment conditions (Figs. 27, 28 and 29).

Table 11 underpins the above observations by means of regression analyses. These models show that the presence of both trust cues (star ratings and profile photos) had no significant effect on the realization of transactions. However, we find that both star

Table 11 Regression models for share of realized transactions, requests sent, and requests received

	DV = Share of realized transactions	DV = Share of users that at least on request	
		Sent	Received
Treatment: star ratings $^{(yes=1,\ no=0)}$	.009	**.042****	.005
	(.021)	(.013)	(.023)
Treatment: profile photos $^{(yes=1,\ no=0)}$	.037	**.032***	.042
	(.021)	(.013)	(.023)
Period $^{(0–5)}$	−.003	.002	−.006
	(.006)	(.004)	(.007)
Intercept	**.900*****	**.935*****	**.926*****
	(.028)	(.017)	(.031)
Observations	24	24	24
R^2	.154	.474	.169

Data on treatment-and-period level (i.e., n = 4 · 6 = 24); DV = dependent variable; standard errors in parentheses; ***
$p < .001$; ** $p < .01$; * $p < .05$

ratings (β = .042; $p < .01$) and profile photos (β = .032; $p < .05$) have positive effects on the share of participants (i.e., consumers) who sent at least one request (averaged by treatment *and* period). However, we do not find any significant influence of these treatment variables on the fraction of participants who *received* at least one request (i.e., providers). This suggests that the additionally sent requests are not spread out evenly across providers but concentrate on those who already receive requests from other consumers. Last, note that period did not affect the dependent variable in any of these models.

Appendix C: Power Analysis

To assess our sample's power, we used a Monte Carlo simulation approach. Specifically, we simulated data sets following the treatment and data structure at hand (multiple observations per subject, nested in sessions). On these data, we conducted mixed effect regressions (fixed effects for treatment and period, random effects (i.e., intercepts) for subject and session). Specifically, for period, we used an effect of 0.02. Within-subject and between-subject variance was set to $\sigma_{within} = 0.1$, $\sigma_{between} = 0.2$). We varied the treatment effect (of photos/ ratings) between 0.15 and 0.35 in steps of 0.05–which yielded effect sizes (f^2) between 0.12 and 0.61. For the simulation, we used 1,000 iterations for each parameter setup. This resulted in the assessment depicted below. As shown there, given the experimental treatment and data structure, our sample (i.e., 12 sessions à six providers/consumers à six periods) is sufficiently large to detect an effect size of 0.21 with power of about 95% and an effect size of 0.12 with power of 80% (Fig. 30).

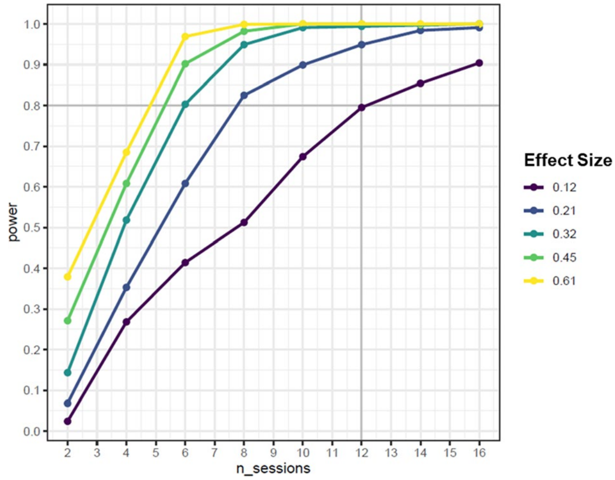


Fig. 30 Power analysis ($n = 36$ * n_sessions)

Appendix D: Randomization Check

See Table 12

Table 12 Randomization check regression results

	Age *(OLS)*		Is female *(logistic)*		Has experience (as host) *(logistic)*		Has experience (as guest) *(logistic)*	
Profile Photo	0.292	0.500	−0.352	−0.357	−0.117	0.000	0.333	0.801
	(.494)	(.701)	(.344)	(.489)	(.343)	(.478)	(.366)	(.527)
Star Rating	0.097	0.306	0.118	0.113	−0.234	−0.116	0.067	0.504
	(.494)	(.701)	(.343)	(.476)	(.343)	(.481)	(.365)	(.505)
Photo × Rating		−0.417		0.009		−0.241		−0.935
		(.991)		(.687)		(.686)		(.740)
Intercept	21.965***	21.861***	−0.339	−0.336	−0.278	−0.336	0.660*	0.452
	(.428)	(.496)	(.294)	(.338)	(.293)	(.338)	(.308)	(.342)
Observations	144	144	144	144	144	144	144	144
R^2	0.003	0.004						
Log Likelihood			−95.642	−95.642	−95.935	−95.873	−87.362	−86.555
Akaike Inf. Crit			197.284	199.284	197.87	199.747	180.725	181.109

*$p<0.05$; **$p<0.01$; ***$p<0.001$

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Declarations

Conflict of interest The authors declare that there are no conflicts of interest.

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