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Research Paper

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Abstract

With the ever-growing popularity of online shopping, platform environments providing access to products by multiple sellers increasingly attract users. To reduce information asymmetry and enhance user trust, platform actors provide signals such as star reviews to demonstrate their trustworthiness. This work investigates the influence of trust signals from different sources (on the platform itself vs. on external third-party review sites) and for different targets (platform provider vs. seller) on users' trust formation in multi-sided e-commerce platforms. We conduct a choice-based conjoint analysis based on data from 81 participants. Our results show that users weigh external signals stronger than internal ones when building trust. Also, trust signals for sellers have a higher impact on users' trust than platform provider signals. Signal discrepancies between internal and external reviews are especially harmful to the platform provider. These insights extend prior knowledge on trust formation and its impacting factors on e-commerce platforms.

Keywords. Trust Formation, Multi-Sided Platform, Online Reviews, Signal Discrepancy, Conjoint Analysis

1 Introduction

With the rise of digitalization, the influence of e-commerce as a main distribution channel for physical goods grew rapidly (Kim, 2008; Fang *et al.*, 2014). It is estimated that e-commerce in Europe will reach $1.3 trillion in revenue by 2027, growing by 14.5% each year (Statista, 2023). To facilitate demand-supply matches between potential customers and sellers, multi-sided platforms started to gain importance in the last few years (Abdelkafi *et al.*, 2019). Multi-sided e-commerce platforms consist of sellers, buyers, and a platform provider operating as intermediary between potential buyers and sellers by offering communication services and coordination to match the demand and supply of goods (Duch-Brown, 2017). Such platforms thereby increase transaction efficiency while maintaining low transaction costs (Duch-Brown, 2017). Yet, given their temporal and spatial separation, relationships between buyers and sellers are often characterized by uncertainty and fear of opportunism, making trust as an enabling factor salient in e-commerce settings (Pavlou and Gefen, 2004; Chen *et al.*, 2015). According to signaling theory, sellers can utilize signals to steer buyers' perception of product and seller quality, thereby creating trust (Spence, 1973; Teubner, Hawlitschek and Adam, 2019). Therefore, strong trust-signaling elements are necessary to reduce perceived risk and increase information quality on multi-sided platforms.

To enable trust-building, there is a plethora of trust-signaling elements in an online environment, ranging from textual to star reviews or trusted third-party symbols (e.g., quality labels) (Casado-Aranda, Dimoka and Sánchez-Fernández, 2019). One popular facilitator for trust is the assessment of a third party, such as prior transaction partners (Teubner, Adam and Hawlitschek, 2020). Customer reviews are well-known and reliable sources of information and are proven to be an enabler for trust, as they mimic social interaction (Kim, Ferrin and Rao, 2009; Teubner, Adam and Hawlitschek, 2020). These systems contain users' aggregated review scores, usually displayed through star reviews (Hesse et al. 2020a) and strongly influence the user's perception of trustworthiness—even more than expert reviews or consultants (Chen *et al.*, 2015). Consequently, they are one determining factor for purchasing behavior, as they are seen as relatively unbiased and independent of a platform's marketing strategy (Li *et al.*, 2015). In multi-sided e-commerce platforms, two possible objects can be the target of a review score and hence of trust: The intermediating platform provider and the sellers (Hong and Cho, 2011). Additionally, two main types of sources for review information can be identified. On the one hand, review information can be provided on the platform itself, on the other hand, external websites that specialize in user ratings, like Yelp or Trustpilot, nowadays provide users a variety of review information online. These external rating websites can be particularly helpful if an intended purchase is not to take place on a well-established e-commerce platform, but a specialized, lesser-known niche platform (e.g., used car platforms or luxury trading platforms). While platforms can control the trust-signaling contents on their own website, they have little to no influence on their reviews on external websites, potentially leading to differences in the review information on-site and off-site.

In current research, we see first attempts to explain customers' trust formation towards intermediaries or sellers. Relying on trust transfer theory, Chen et al. (2015) show that trust is transferrable between platforms and sellers and that website quality and institutional mechanisms influence this relationship. In alignment with signaling theory, Teubner et al. (2020) furthermore demonstrate that a mismatch between review information can be harmful to user trust and that information consistency is important. Hesse et al. (2020a) were among the first to differentiate between review information on marketplaces and from external websites. Their work on reputation portability, describing the concept of leveraging reputation from an external platform by utilizing it as a trust signal on another platform, shows that imported reputation influences trust building positively or negatively, depending on the score of the review values (Hesse et al. 2021). With our research, we want to bridge the gap between trust transfer theory (assuming trust transfer between different targets) and reputation portability (postulating transferability of trust between different sources) in multi-sided platform settings: We consequently assume that the simultaneous presence of trust signals for the platform provider as well as the seller, presented on a website as well as on an external third-party review websites have distinct impacts on customers' trust formation. Hence, we define the following research question:

RQ: *What is the influence of trust signals from different sources (i.e., internal vs. external) and for different targets (i.e., platform provider vs. seller) on users' trust formation in multi-sided e-commerce platforms?*

To answer this research question, we conduct an online experiment with 81 participants and analyze the data by applying a conjoint analysis. A conjoint analysis is a well-established discrete choice framework for evaluating consumer preferences between multi-attribute alternatives. In our case, the conjoint analysis allows us to make statements about the impact of a single trust signal on a user's final trust evaluation. In particular, we investigate how star reviews as trust signal for different targets on a multi-sided e-commerce platform (platform provider and seller) and from different sources (internal information on the platform vs. external information from a third-party review site) impact the final trust evaluation of a user. Further, we analyze how discrepancies between these reviews impact users' trust. From a theoretical perspective, this research contributes to understanding trust formation on multi-sided platforms—a phenomenon currently gaining importance in retail and beyond (e.g., data platforms in B2B settings). We further complement existing research by analyzing individual trust signals' contribution to a user's overall trust assessment (especially when they are confronted with several—possibly contradicting—trust signals). For platform providers as well as online sellers this research provides practical insights on where to focus attention when improving their trustworthiness with online reviews.

The remainder of this paper is structured as follows: The next section describes the theoretical foundations of trust formation in e-commerce. This is followed by a description of our research design and the conjoint analysis results. We conclude by discussing the implications and limitations of our findings and pointing out potential avenues for future research.

2 Foundations and Related Work

Trust is a multilevel, subjective construct, describing the willingness of a party to be vulnerable to the actions of another party, expecting that the other will perform a benevolent act to the trustor (Mayer, Davis and Schoormann, 1995; Kim, 2014). In an e-commerce context, trust is found to be even more relevant than in physical markets, mainly due to a lack of social signals and information about the other party (Bailey and Bakos, 1997; Reichheld and Schefter, 2000). In this context, McKnight et al. (2002) find trust building in e-commerce settings to be influenced by structural assurance (i.e., consumer perceptions of the safety of the web environment), perceived seller reputation, and perceived web site quality. Given the abundance of offerings in e-commerce, buyers are often confronted with a large amount of—possibly conflicting—information that they must process as part of their trust-building process. Therefore, users seek to find mental shortcuts to reduce information complexity and minimize their cognitive load (Grabner-Kräuter and Kaluscha, 2003). Trust serves as the main mechanism to reduce complexity in uncertain situations (Chien, Chen and Wu, 2013). Oppositely, a lack of trust is one of the most cited reasons for buyers not purchasing in online shops (Lee and Turban, 2001).

Trust relationships can emerge between all three parties involved on a multi-sided e-commerce platform, including buyers and sellers and the platform provider itself (Aljazzaf, Perry and Capretz, 2010). Trust transfer theory describes the cognitive process where an individual's trust is transferred onto a trustee via a familiar third-party target, mainly facilitated through information processing (Chen *et al.*, 2015). Chen et al. (2015) were among the first to utilize trust transfer theory to analyze differences in trust-building regarding the trust target. They find that trust in a marketplace positively affects the trust in the seller, which then positively affects purchase intention. Malak et al. (2021) back these findings and propose that the seller's reputation has a strong positive impact on trust in the seller and a moderate, positive effect on the trust in the marketplace. Yet, they do not investigate how different ratings from internal (i.e., information provided on the marketplace itself) or external (i.e., information provided on third-party sites) sources of information contribute to the trust in the seller (Malak *et al.*, 2021).

Multi-sided e-commerce platforms can provide mechanisms to bridge the trust gap between platform actors, thereby facilitating transactions. We find the topic of trust-building through reviews in e-commerce to become more relevant in recent years (Chua 2014; Weathers et al. 2015), with star reviews being the mainly used type of visual signal in online environments (Kostyk, Leonhardt and Niculescu, 2017). Signaling theory suggests how signals can be utilized to influence how users perceive the seller's and a product's quality, when quality cannot be observed directly (Spence, 1973; Teubner, Adam and Hawlitschek, 2020). Star reviews thereby describe one possible trust signal, based on reputational, transaction-based data, aggregated to easily indicate review sentiment (Al-Natour and Turetken, 2020; Teubner, Adam and Hawlitschek, 2020). It is proposed that higher review scores positively influence consumer trust and satisfaction (Wulff, Hills and Hertwig, 2015).

Interconnections and portability of review signals from external sources are one topic that gained interest within the last few years. This refers to the question of whether the reputation a seller obtains on one platform can act as a trust-enhancing signal when presented on another platform with less review information (Hesse et al. 2020a). By analyzing imported feedback at the platform Bonanza.com, Hesse et al. (2020a) demonstrate an overall negative effect of imported positive feedback from other platforms on sales performance of a seller. These results seem counterintuitive, as the positive influence of higher reviews on consumer trust and intention to buy is widely accepted (Wulff, Hills and Hertwig, 2015). Two possible explanations are proposed: Sellers might be considered to "cherry-pick" their reviews, increasing the level of average reviews to a degree where it is deemed implausible by customers (Hesse et al. 2020a). This hypothesis aligns with Maslowska et al. (2017), who find that very positive reviews can have similar adverse effects as negative reviews. Another possible explanation is that the discrepancies between the reputation on the platform and the imported reputation lead to doubts about the trustworthiness of the reviews altogether. The effects of signal discrepancy are not yet researched in detail. Hesse et al. (2020b) provide first insights into how signal discrepancy might affect customer trust and show that a higher review discrepancy is detrimental to purchase intentions and explain this effect with human risk aversion.

3 Research Design and Methodology

With this research, we aim to understand how trust signals from different sources and for different targets are aggregated to an overall trust assessment in a multi-sided platform setting. We approach this question using a conjoint analysis—a methodology for evaluating consumer preferences and analyzing trade-offs between multi-attribute alternatives. In this section, we consequently describe our research design and the conjoint analysis, elaborate on the procedure of the conjoint experiment, and provide details on our sample.

3.1 Design of the Conjoint Analysis

A multi-sided e-commerce platform describes the combination of an intermediary platform provider (also often referred to as 'marketplace' in the e-commerce setting) (e.g., Amazon), a set of sellers, and potential buyers. In such a setting, trust signals can pertain to two different targets: the seller or the platform provider as an intermediary. In general, trust signals are provided on the e-commerce platform itself. Additionally, trust signals can be retrieved from external third-party review websites that offer review signals for platform providers and sellers. We consequently differentiate between two sources of trust signals: internal and external. This is of high practical relevance, as review websites become more common with the rise of online shopping indicating that users tend to research several sources of information before a decision (Canvas8, 2020; Guillet and Law, 2010). Furthermore, there is evidence that review information is importable from external websites to an internal website (Teubner, Adam and Hawlitschek, 2020). Our approach can be seen as a facet of portability without actually importing the information but keeping the information sources separate and making both sources available simultaneously.

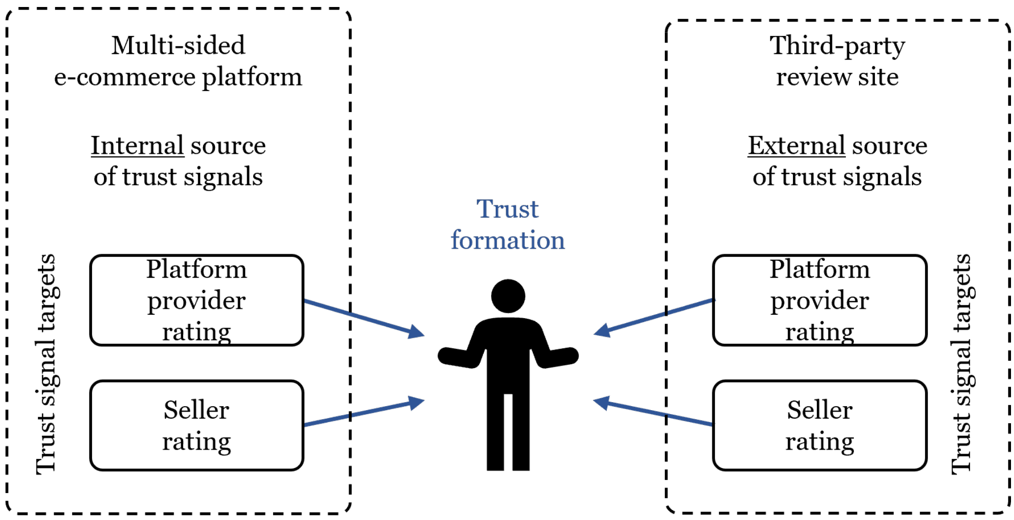

Figure 1. Schematic Illustration of the Research Design.

Generally, signaling theory suggests that all four trust signals contribute to the trust-forming process, but the extent to which signals presented simultaneously contribute has not yet been studied. In particular, differentiating between the two sources of trust signals with different purposes becomes more and more relevant. It is argued that information is perceived as more credible with a higher degree of source independence (Fuller, Serva and Benamati, 2007). Moreover, investigating the different targets is essential as it is shown that users cognitively differentiate between the platform provider itself and the seller when forming trust (Hong & Cho, 2011). Figure 1 visualizes the overarching focus of this research endeavor, including the influencing factors to be considered.

We carry out a choice-based conjoint analysis to analyze how user trust is formed and impacted by online reviews as trust signals. The conjoint analysis is a well-established discrete choice framework for evaluating consumer preferences between multi-attribute alternatives and a commonly used technique for analyzing buyers' trade-offs among competing products or suppliers (Green, Krieger and Wind, 2001). Although mainly applied in Marketing Research so far, it has several advantages in the context of mass-market IS and has become more popular in the field within recent years, as it allows the evaluation of products, resembling real-world decisions and therefore ensuring better user acceptance (Schaupp and Bélanger, 2005; Naous and Legner, 2017). In our case, using a conjoint analysis allows us to make inferences about the underlying value system by enabling participants to decompose their overall trust evaluation of the different attributes. This way, the relative importance of individual trust signals and sources can be evaluated.

A conjoint experiment is designed to gather relevant data on users' choices when confronted with different types of trust signaling information. In assessing user's choices given a set of trust signals, e draw on previous studies that cite trust as a direct antecedent to purchase intention (Lu, Fan and Zhou, 2016). As trust signals, we rely on user reviews displayed as star reviews. As related work demonstrated, star reviews are a commonly used and well-understood method to facilitate the trust-building of users (Kostyk, Leonhardt and Niculescu, 2017; Casado-Aranda, Dimoka and Sánchez-Fernández, 2019). We distinguish between two different targets of a review (i.e., review of the seller vs. review of the platform provider) and two different sources (i.e., reviews displayed directly on the marketplace site vs. reviews displayed on an external site such as TrustPilot). This results in four combinations of attributes, as displayed in Table .

Attribute	**Target of the Review**	**Source**	**Levels**	**Occurrence**
Internal Platform Provider Signal	Platform Provider	Internal/Platform	High (5 Stars), Low (3 Stars)	Mandatory
Internal Seller Signal	Seller	Internal/Platform	High (5 Stars), Low (3 Stars)	Mandatory
External Platform Provider Signal	Platform Provider	External/Third-Party Review Site	High (5 Stars), Low (3 Stars)	Optional
External Seller Signal	Seller	External/Third-Party Review Site	High (5 Stars), Low (3 Stars)	Optional

Table 1. Attributes Integrated into the Conjoint Analysis.

All attributes are designed to take two levels: high and low. These two levels are represented by an average value of five or three stars. These numbers of stars are chosen as they have been demonstrated to be perceived as discrepant while still taking skewness toward positive ratings in online environments into account (Schoenmüller, Netzer and Stahl, 2018). The levels were further pre-validated in a pretest with six participants confirming the anticipated user perception. While the internal reviews (i.e., ratings of the platform provider and the seller) are presented to participants in all choice options, external reviews from a third-party review site are optional in our research design (i.e., there will be choice options with only internal reviews).

3.2 Procedure

To conduct the conjoint analysis, we collect data in the form of a choice-based experiment (Green, Krieger and Wind, 2001). The experiment is implemented with the online survey tool SoSciSurvey. After instructing participants about the study, their task, and the concept of star reviews, they are asked to imagine being a multi-sided e-commerce platform user wanting to buy a product. The product to be purchased was not specified, but pictures showed a blurred watch. They are then provided with choice options with different star reviews for a fictional marketplace (i.e., the platform provider) and a fictional seller. We apply a full factorial design, i.e., a participant is confronted with choice options that depict all four attributes (and their absence) simultaneously, as presented in Table . A choice set consists of two alternative options. Hence, a participant must decide between two potential multi-sided e-commerce platforms with different attribute levels, i.e., different star reviews for platform provider and seller. Figure 2 visualizes how trust in the multi-sided platform is investigated in the online experiment. The left part of an option is included in every choice option and represents review information that is present on the e-commerce platform itself. On this webpage, an average star review (either three or five stars) for the platform provider and a seller is shown. The right part of an option represents an external third-party review website. It provides an additional average star review for the platform provider and the seller. To be able to test the effect of having external reviews at hand, there are choice settings without having the right part (Figure 2) displayed. The participants are not provided with information on how many reviews contribute to the average star review or about the identity of the reviewers. The position of the reviews and review targets remains fixed. Seller and platform provider were named as generically as possible to avoid priming participants: Seller X and Marketplace.com. For the external review website, we chose a describing name to ensure participants understand the concept of the external third-party review website by leaning on names typically used for these types of websites, for example, TrustPilot (2022). The product to buy and product descriptions were blurred to not interfere with the decision process.

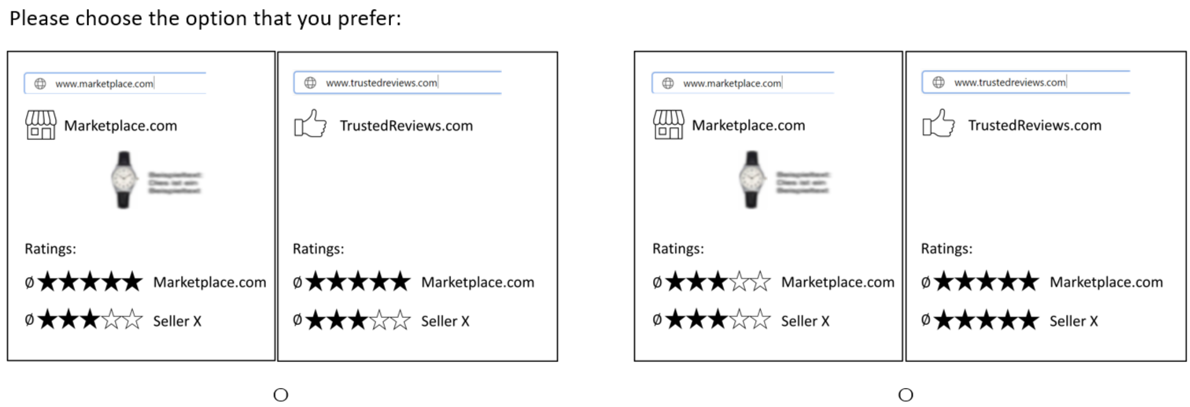

Figure 2. Example of a Decision in the Conjoint Experiment.

To minimize participants' cognitive effort and maintain their motivation, each participant is guided through five rounds of choices between two randomly drawn attribute combinations. The combinations differ in two regards: Firstly, the existence of the external third-party trust signals by the fictional third-party review website TrustedReviews, and secondly, the level of the star reviews for the platform provider and the seller, which was binary coded as high (equaling five stars) and low (three stars). In total, 18 choice options with different attribute combinations are tested, as shown in Appendix A. After the five choice rounds, a questionnaire is included to collect additional data on participants' age (Everard and Galletta, 2005), gender (Everard and Galletta, 2005), education (Everard and Galletta, 2005), internet affinity (Everard and Galletta, 2005), disposition to trust (Kim, Ferrin and Rao, 2009), and risk affinity (Dohmen *et al.*, 2009) as control variables.

3.3 Participants

In recruiting our participants, we aim at getting a sample with adequate variance regarding their demographics. Therefore, participants were recruited via social media channels and an online survey tool. The participants were not incentivized to participate. In total, 208 responses were collected between 09/2021 and 10/2021; whereof 98 were complete. Twelve participants were excluded because they did not pass the attention check, five participants answered in patterns and were sorted out after careful revision. This led to 81 complete data sets. The participants' age ranges from 18 to 66 years (mean: 34) within the final sample. 42% are female, 54% male, 4% others. 70% have a university degree, 17% a high school diploma, 7% a secondary school diploma, and 6% a college entrance qualification. 48% of the participants are employed, 40% are students, 9% are officials, 2% are pensioners or self-employed, and 1% are pupils. The average income in the sample was 2,100 Euro with a median of 2,000 Euro. The mean internet affinity, which depicts how experienced they feel about using the internet is at 5.40 (SD=1.42) measured on a 7-point Likert scale. The mean disposition to trust equals 4.40 (SD=1.11) and describes their general tendency to trust others. 4.40 (SD=1.52) is the mean risk affinity, i.e., a participant's general openness to taking risks.

4 Analysis of Empirical Results

Using a conjoint analysis allows us to analyze the effect of different trust signals on consumers' trust formation on multi-sided platforms. The conjoint analysis estimates the part-worth utility changes between attribute levels and allows us to calculate the relative importance of an attribute. For the analysis, the attribute levels are dummy-coded. For example, for the trust signal of an Internal Platform Provider Signal, the high (five-star) level is encoded as 0 and the low (three-star) level as 1. Each attribute combination contains at least the Internal Platform Provider Signal and the Internal Seller Signal, complemented by the two external signals. An additional dummy variable is added to model whether external reviews are present or not. The results of the conjoint analysis need to be interpreted relative to a base set of attributes. We use the attribute level combination with two high internal signals (five-star Internal Platform Provider Signal and five-star Internal Seller Signal) and no external signals as a baseline, as it is the most straightforward combination that was provided (i.e., it has only two instead of four attributes and no signal discrepancies). Therefore, the utility change of each attribute can be interpreted relative to the base attribute level combination, and their magnitude can be compared relative to each other. Further, the choice-based conjoint data is analyzed using the multinomial logit (MNL) model, which is based on the random utility model and a standard method to analyze choice-based data (Elshiewy et al. 2017; McFadden 1973). The coefficients are estimated with maximum likelihood estimation resulting in part-worth utilities and the standard error for each attribute. The intercept in the MNL model captures the average utility offset for the base treatment. All choices of a participant are interpreted as individual choices. Thus, learning effects were not considered due to the limited number of rounds per participant. Regarding model fit, a McFadden R^2 of 0.07 suggests an acceptable fit, especially since we use field data observing human behavior (McFadden 1973).

To avoid overfitting, we carry out the analysis in three steps and add additional attributes and interactions gradually (first step: internal signals only, second step: internal and external signals, third step: internal and external signals with interaction effects). In the first step, we start the analysis with a reduced model, considering only the internal platform provider and seller signal. Other signals are added in the following steps. To do so, we calculate the part-worth utilities for each attribute, which describe the average change in utility if the level of an attribute is changed (e.g., if the Internal Platform Provider Signal changes from high to low). Based on the utility changes, the relative importance of each attribute is calculated. This allows ranking the attributes regarding their relative impact on the overall utility, i.e., the final trust evaluation (Orme, 2002). Table 2 summarizes the results of the first analysis step and the utility changes for attribute level changes in internal trust signals. While the shift from a high to a low platform provider signal has no significant impact on overall utility ($p>0.1$), there is a significant decrease in the user's utility by 0.28 points when the seller signal is lowered from five to three stars

($p<0.05$). Therefore, one can argue that reducing the Internal Seller Signal impacts users' trust in the buying setting. This is also reflected in the relative importance of 81.4% for the Internal Seller Signal. However, in this first analysis step, neither the external signals nor possible signal discrepancies are considered in the model. To gain insights into these two effects, they are added to the scope of analysis in the following two steps.

	Level Change	Part-worth Utility	Std. Error	p-value	Relative Importance
Intercept	-	0.04	0.10	0.69	-
Internal Platform Provider Signal	High → Low	-0.06	0.14	0.65	18.6%
Internal Seller Signal	High → Low	-0.28	0.14	0.05***	81.4%
Note: *p < 0.10; **p < 0.05; ***p < 0.01					

Table 2. Results of the Conjoint Analysis with Internal Signals Only.

Second, we include internal and external trust signals for the platform provider and the seller, which is depicted in Table . The variable Existence of External Signals models whether the external trust signal for Platform Provider and Seller is shown to participants. Hence, Existence of External Signals takes the level "off" if no external trust signals are presented to a user and "on" if both external trust signals are presented and adopt high levels (five stars). If a user gets presented with two high external trust signals, this has a strong positive influence on the user's utility of +1.09 points ($p<0.001$). With relative importance of 38.5%, it is also the most influential attribute. On the other hand, if one of the external signals is lowered, which is represented by the variables External Platform Provider Signal and External Seller Signal, the user's utility is reduced by a similar degree with values of -0.57 and -0.54 ($p<0.001$ for both). When comparing the impact of low internal signals and low external signals, we see that even though all signals seem to have a negative effect on utility when being lowered, the external signals have a higher impact with a relative importance of 20.1% and 19.1% compared to 14.8% and 7.4% for the internal signals.

	Level Change	Part-worth Utility	Std. Error	p-value	Relative Importance
Intercept	-	0.01	0.10	0.89	-
Internal Platform Provider Signal	High → Low	-0.21	0.15	0.15	7.4%
Internal Seller Signal	High → Low	-0.42	0.15	0.00***	14.8%
Existence of External Signals	Off → On	1.09	0.23	0.00***	38.5%
External Platform Provider Signal	High → Low	-0.57	0.16	0.00***	20.1%
External Seller Signal	High → Low	-0.54	0.16	0.00***	19.1%
Note: *p < 0.10; **p < 0.05; ***p < 0.01					

Table 3. Results of the Conjoint Analysis for Internal and External Signals.

In the third step, we analyze the effect of signal discrepancies on trust formation. A signal discrepancy exists when the internal and external signals of the platform provider or the seller differ. We take both possible directions of discrepancies into account (e.g., a high internal platform provider signal in combination with a low external platform provider signal and vice versa). To calculate the effect of discrepant information, possible interaction effects between different signals must be included in the conjoint model. This way, one can see whether combinations of attribute level changes of two trust signals might have other effects than the attribute level change of a trust signal on their own. In Table , the variables ‘Internal AND External Platform Provider Signals’ and ‘Internal AND External Seller Signals’ measure the impact of either a low internal signal for both seller and platform provider or a low external signal for both. With the introduction of the interaction effects into the model, the main effects as tested in the previous iterations remain similar in their direction and extent.

To extract the utility change caused by a signal discrepancy between the internal and external platform provider signal, the utility change of the interaction effect is added to the utility change when the attribute’s level is set from high to low. This is a valid approach since the utility function in a multinominal logit model is linear. Therefore, the total utility of any attribute combination is given by the sum of each attribute’s individual utility change. Hence, given a high internal and a low external platform provider signal, the utility change for removing this discrepancy (by a level change of the internal signal to ‘low’) equals +0.16. This reflects the sum of the utility change of the internal platform provider signal (-0.47) and the interaction effect ‘Internal AND External Platform Provider Signals’ (+0.63). Therefore, removing the signal discrepancy—even if this means that one of the ratings is lowered to 3 stars—is associated with a gain in utility. It consequently positively influences users’ trust. For signal discrepancies in the seller signal, we cannot make any assumptions, as the interaction effect of the seller ‘Internal AND External Seller Signals’ is not significant (p>0.1). Since extant literature has already investigated the effect of a signal discrepancy between the platform provider and the seller (Chen *et al.*, 2015), this type of signal discrepancy was not our research’s focus.

To test the robustness of our findings, we further controlled for age (Everard and Galletta, 2005), gender (Everard and Galletta, 2005), education (Everard and Galletta, 2005), internet affinity (Everard and Galletta, 2005), disposition to trust (Kim, Ferrin and Rao, 2009), and risk affinity (Dohmen *et al.*, 2009). When including the control variables, we did not see any changes in significance for the other variables, and none of the control variables had a significant influence on trust formation.

	Level Change	**Part-worth Utility**	**Std. Error**	**p-value**	**Relative Importance**
Intercept	-	0.03	0.11	0.80	-
Internal Platform Provider Signal	High → Low	-0.47	0.20	0.02**	10.1%
Internal Seller Signal	High → Low	-0.55	0.20	0.01***	11.8%
Existence of External Signals	Off → On	1.16	0.23	0.00***	24.8%
External Platform Provider Signal	High → Low	-0.84	0.21	0.06*	18.0%
External Seller Signal	High → Low	-0.68	0.22	0.00***	14.6%
Internal AND External Platform Provider Signals	High → Low	0.63	0.31	0.04**	13.5%
Internal AND External Seller Signals	High → Low	0.34	0.33	0.30	7.3%
Note: *p < 0.10; **p < 0.05; ***p < 0.01					

Table 4. Results of the Conjoint Analysis with Interaction Effects.

In summary, the conjoint analysis suggests that a low internal seller signal has a stronger negative impact on the user’s trust evaluation than a low internal platform provider signal. In contrast, for the external signals, the platform provider signal has a stronger impact. We also see that external signals have a higher impact on the user's utility than internal ones. Especially when external signals are lower than the internal signals and thus generate a signal discrepancy, we observe a strong negative impact on utility.

5 Discussion

The wide variety of trust signals on multi-sided e-commerce platforms led to the call for a comparison of the quality of said signals (Qiu, Parigi and Abrahao, 2018; Casado-Aranda, Dimoka and Sánchez-Fernández, 2019). Previous research mainly focused on either the comparison of the effect of different types of trust signals, like visual or textual signals (Chen et al. 2015; Kim 2008), or the transfer of trust by importing review signals from other websites and displaying them on-site (Hesse and Teubner, 2020; Teubner, Adam and Hawlitschek, 2020). Our research extends the current body of research by differentiating between external review signals from a third-party review website and internal signals while also taking the two main trust targets on a multi-sided e-commerce platform into account, namely the platform provider and the seller.

The conjoint-based analysis offers detailed insight regarding our research question on how trust signals for different sources influence users' trust formation in multi-sided e-commerce platforms. We find the presence of external signals from a third-party review website to strongly impact utility. Hence, a user's final trust evaluation is largely formed by external signals compared to internal ones. This is generally in line with the concept of signaling theory, which postulates that the presence of two or more signals requires the users to assess all signals for their trustworthiness (Hesse, Teubner and Adam, 2021). Thus, when additionally being confronted with trust signals from an external third-party review website, it seems intrinsically reasonable for users to take those signals into account and evaluate them together with the internal ones when forming trust. Further, in alignment with de Haan et al. (2008), we see that the presence of additional signals strongly increases trust in a choice option. This follows the logic of inherent noisiness of signals that makes signals rather an indicator of trustworthiness instead of proof (de Haan, Offerman and Sloof, 2008; Hesse, Teubner and Adam, 2021). A possible explanation for why the external signal has such a strong influence on trust-building compared to internal signals only, might be due to the impression that external sources are perceived as less corrupted and therefore as a trustworthy source of assurance (Fang *et al.*, 2014). However, this is only the case if the additional information is congruent with the prior information, supporting the finding of Hesse et al. (2021). They argue that an imported rating for a seller with no internal reviews rating is only beneficial if its value is sufficiently high and even harmful in other cases (Hesse et al. 2021).

When we compare the results for each target separately, we see that users gain more utility from the internal seller signal than from the internal platform provider signal. A possible explanation for this is that the users might consider the platform provider as more difficult to replace than a seller. Consequently, they are more interested in finding a trustworthy seller on a fixed platform instead of considering switching to alternative platforms. Additionally, an internal platform provider signal might be interpreted as a self-description or advertisement. This type of conventional signal (i.e., self-descriptions or advertising badges) has proven to be less reliable to users than signals like customer reviews, which are less likely to be influenced or manipulated by the party affected by the signal (e.g., from an external source) (Mavlanova, Benbunan-Fich and Koufaris, 2012).

In contrast, by looking at the two external signals, we find the platform provider review to have a stronger impact on the users' utility than the seller review. From a practical perspective, this seems logical, as external sources of information might imply having alternatives in platform providers to choose from. This can lead a user to scrutinize their decision to buy on a specific multi-sided e-commerce platform with a poorly rated platform provider and to consider other alternatives. In contrast, when only internal information is available, the specific platform provider might be assumed to be fixed, and a user rather optimizes for a seller with a high review. This argumentation is supported by the results we see when reducing single signals from the 5-star level to the 3-star level: We find that a low external platform provider signal is almost twice as detrimental to users' utility as a low internal platform provider signal. We see an effect in the same direction for the seller signal, but to a lower degree. This can to some extent be explained by the fact that users might assume a seller to less likely have a direct influence on their internal reviews than the platform provider, who is typically responsible for the platform design and the information that is presented to users.

Finally, we can get first insights into how discrepant signals for the same target affect users' trust-building. While a discrepancy generally harms trust, a discrepancy in platform provider signals with a high internal and a low external signal is especially harmful. This is in line with the findings of Hesse et al. (2020b), who argue that a discrepancy between imported and on-site trust signals for a seller is detrimental to purchase intentions, which are mediated by trust. Surprisingly, a discrepancy between internal and external signals for the platform provider is even worse than two congruent low signals. Hence, discrepant internal and external signals—being a potential indicator of faked reviews—seem to be associated with higher risks (Hesse et al. 2020b) that eventually lead to losses in trust. The fact that this effect is only significant for discrepancies in the platform provider signals but not in those of sellers again fits with the previously stated observations that in the presence of third-party signals, sellers have a smaller influence on trust formation than the platform provider.

6 Conclusion

With this study, we aimed to understand users' trust formation on a multi-sided e-commerce platform by investigating the influence of trust signals with differences in trust targets (seller vs. platform provider) and signal source (internal vs. external). To achieve this, we conducted a choice-based conjoint analysis with 81 participants. They were asked to decide between two options with different combinations of high and low star reviews. Our results show that all four trust signals provided influence a user's overall trust evaluation. A discrepancy between these signals negatively impacts trust, especially when it comes to platform provider signals. In general, seller signals have a higher impact on trust than platform provider signals and external signals have a higher one than internal signals. These findings imply theoretical and managerial implications described in the following sections, concluded with limitations of our work and an outlook for further research.

From a theoretical perspective, our research provides four important contributions: First, we contribute to the understanding of influencing factors on the formation of a user's trust in the context of multi-sided platforms. In an extension of existing literature, this study investigates a multi-sided platform as the compound of different actors for which a user has diverse information to rely on when forming their evaluation on whether to trust a specific setting. Using a conjoint analysis, we are able to assess individual trust signals' contribution to a user's overall trust assessment. In doing so, we are pushing our discipline's theoretical knowledge further toward real-world applications. By adopting a signaling theory lens, we investigate how star reviews as trust signals for different targets on a multi-sided e-commerce platform (platform provider and seller) and from different sources (internal information on the platform vs. external information from a third-party review site) impact the final trust evaluation of a user. In this case, the conjoint analysis allows us to discriminate between the single signals' influence on a user's overall trust. Second, we explicitly distinguish between the sources of trust signals and their impact. In investigating online reviews directly on the platform at hand and from external sources, we complement prior studies on reputation portability. Instead of explicitly importing online reviews as reputation signals from other platforms, our study assumes an implicit reputation transfer when a user evaluates the trust signals from external sources. Third, we illuminate how signal discrepancy impacts users' trust. We thereby contribute to research on signal discrepancy by detaching it from the concept of trust transfer as introduced by Hesse et al. (2020b) and evaluating discrepant signals from distinct sources. Adding to the current body of knowledge, we particularly investigate the effects of discrepant signals from separate sources (i.e., internal and external trust signals). Our study reveals that a signal discrepancy between two trust sources for a platform provider is even worse than two low but consistent ratings. Last, the paper also provides a methodological contribution by proposing conjoint analysis as a method for the evaluation of trust within e-commerce settings. While this method is still mainly used for product design in marketing studies, its popularity is increasing within the IS field. So, exploring the different research areas that conjoint analyses can cover contributes to the methodology itself as a demonstration and empirical evidence.

From a practical perspective, recommendations on how to facilitate trust-formation on multi-sided e-commerce platforms can be derived: While all four trust signals—internal vs. external and for the seller vs. for the platform provider—are influential towards a user's trust formation, we found a strong impact of external reviews on users' trust in the platform provider and the seller (especially in comparison to internal reviews). Therefore, we advise platform providers and sellers to keep track of their ratings on external websites and take measures to maintain high external reviews. For example, this could be achieved by directing users towards external review websites to leave a review after a purchase. Further, this is important as we found signal discrepancies to be harmful, especially in settings with a high trust signal on the platform and a low signal on the external third-party review website. In extreme cases of discrepancies, platform providers should even consider accepting a lower average signal on their own platform or website to lower signal discrepancy and to consequently appear more trustworthy. Regarding the internal platform provider signal, we see the lowest impact on trust formation. Hence, platform providers should be aware of the fact that this type of information might be perceived as a mere advertisement with a low informational value for trust-building.

Despite aiming for a holistic perspective on trust-building on multi-sided e-commerce platforms, some limitations were necessary for this study that still provide directions for future research. First, our research focused on average star reviews as single type of trust signal, since this is the most common visual signal in the online environment (Mavlanova, Benbunan-Fich and Koufaris, 2012). Our approach of combining different types of trust signals could be extended to other kinds of feedback: Regarding visual feedback, a possible adaption could be made by looking into product pictures uploaded by the seller compared to photos uploaded by recent buyers. Bente et al. (2012) already suggest that seller photos impact buyer trust, so an extension of our study to build on these findings might be promising. Other feedback signals, such as textual feedback, might as well be considered to further investigate the interplay of more heterogeneous information.

Further, by choosing conjoint analysis as the methodological approach, we equated trust as the target variable with user preferences in a choice situation. Although only different star ratings and no other product attributes were included in the decision situation, and previous studies have presented trust as an antecedent of purchase decisions (Lu, Fan and Zhou, 2016), a minimal bias may exist at this point. Accordingly, we encourage future studies that verify the results using direct measurement methods for trust (e.g., traditional questionnaires).

Moreover, we focused on two levels of star reviews only, high and low, represented by five and three stars. By applying a finely granular partitioning, for example, levels of 0.5 stars as proposed by Hesse et al. (2020a), one could investigate whether the increase in user trust is proportional to an increase in reviews or whether bands of reviews exist in which trust remains relatively stable. While we focused on trust in general, a further division might also bear potential: Either by differentiating between trust types such as economic, functional, emotional, and social values as proposed by Payne and Frow (2020) or by regarding the different phases of trust-building (i.e., pre-purchase, during purchase and post-purchase) as described by Mavlanova et al. (2012). In our research setup, the users were not provided with additional information on the credibility of reviews. By expanding the research question in this regard, one could further investigate how users build trust by seeing trust signals with different levels of credibility.

Additionally, by modeling the uncertainty users face in an online shopping scenario and consequently further trigger the necessity for trust-building, monetary incentivization or penalties for choices in the conjoint experiment, can be promising next steps. This way, participants are confronted with immediate consequences for their behavior, resulting in a closer resemblance to real-life behavior (Johnson and Mislin, 2011). Further, it might be interesting to reiterate on the designs developed for this research.

While the focus was to provide a minimalistic, easy-to-understand setup, a more natural environment, for example, by providing two separate browser tabs for participants to switch freely, could help them to better imagine the proposed scenario (Anderson and McLean, 2019).

Appendix A: Overview of the Attribute Combinations

Combination No.	**Internal Platform Provider Signal**	**Internal Seller Signal**	**External Platform Provider Signal**	**External Seller Signal**
1	High	High	High	High
2	High	High	High	Low
3	High	High	Low	High
4	High	Low	High	High
5	Low	High	High	High
6	Low	Low	High	High
7	Low	High	Low	High
8	Low	High	High	Low
9	High	High	Low	Low
10	High	Low	High	Low
11	High	Low	Low	High
12	Low	Low	Low	High
13	Low	High	Low	Low
14	High	Low	Low	Low
15	Low	Low	High	Low
16	High	High	/	/
17	High	Low	/	/
18	Low	High	/	/

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