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Signals of Competence and Warmth on E-Commerce Platforms

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Abstract: E-commerce platforms generally provide various functions that can be adopted as signals for online sellers to convey implicit information to customers to promote sales. In this article, based on signaling theory and the stereotype content model, we categorize e-commerce signals into two types: signals of competence and signals of warmth. Signals of competence refer to the platform functions or mechanisms that can be leveraged by online sellers to indirectly convey information about their capabilities, such as promised delivery times and free return days. Signals of warmth refer to the platform functions or mechanisms that can be leveraged by online sellers to indirectly convey information about their kindness and care, such as the availability of online customer service agents. We explore the impacts of the two different types of signals on product sales for sellers with different credit rating levels. The empirical analysis is conducted on China's largest e-commerce platform, Taobao.com. The results show that online sellers with higher credit ratings should focus more on signals of warmth, while those with median and lower credit ratings should concentrate more on signals of competence. This study provides a theoretical framework that explains the effects of signaling on e-commerce platforms and may facilitate further exploration on signaling mechanisms. Our findings also provide implications for online sellers in terms of how to better utilize various signals as well as for e-commerce platforms on designing more effective supporting functions.

Keywords: signaling theory, stereotype content model, signal of competence, signal of warmth, online sellers

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1 Introduction

To increase customers' trust and promote sales, e-commerce platforms provide various functions to support online sellers in conveying signals about themselves and their products to customers, such as online customer service and a "more-than-seven-days free return" icon. One of the greatest challenges for online sellers is how to effectively leverage these functions to stand out from thousands of homogeneous competitors on e-commerce platforms (Ou & Chan, 2014). If online sellers use the functions that do not fit their characteristics, it will increase their costs without providing the expected benefits. On the one hand, according to signaling theory (Spence, 1973; Kirmani & Rao, 2009), sending signals requires corresponding costs. On the other hand, customers pay attention to different types of signals according to the characteristics of the online seller. For example, customers may focus more on discounts for famous brands, whereas they concentrate more on the product quality for unfamiliar brands. Therefore, exploring how to convey signals according to online sellers' characteristics will benefit sales.

The use of functions as signals in e-commerce has drawn researchers' attention. However, there are three limitations. First, many of the functions that are discussed in previous research are not optional for online sellers, such as product and online seller ratings (Ou & Chan, 2014; Li, Srinivasan, & Sun, 2009), which are displayed by the platform. According to signaling theory (Spence, 1973), signals should be optional and controllable. Investigating the optional functions is more consistent with the definition of signals and has more practical meaningfulness. Second, researchers mostly classify signals concerning costs (Ou & Chan, 2014; Mavlanova, Benbunan-Fich, & Lang, 2016). However, as signal receivers, customers rarely pay attention to the costs of signals. Thus, it is critical to capture the influences of signals on customers' purchase decisions by classifying signals from the perspective of signal receivers (i.e., customers). Third, previous research investigates the influences of signals without considering online sellers' characteristics. Considering sellers' characteristics may help inform a more personalized and efficient signaling strategy that online sellers convey different types of signals according to their characteristics.

Based on signaling theory and the stereotype content model, this research addresses the aforementioned questions by categorizing e-commerce signals into two types, namely signals of competence and signals of warmth, and exploring the effects of the two types of signals on the sales of sellers with different levels of credit rating. Signals of competence refer to the platform functions or mechanisms that can be leveraged by online sellers to indirectly convey information about their capabilities, such as promised delivery times and free return days. Signals of warmth refer to the platform functions or mechanisms that can be leveraged by online sellers to indirectly convey information about their kindness and care, such as the availability of online customer service agents. Therefore, the research question is: *what are the effects of the two types of signals on the sales of online sellers with different credit rating levels?*

Based on the data from Taobao.com, the empirical results suggest that online sellers with higher credit ratings should focus more on signals of warmth while those with median and lower credit ratings should concentrate more on signals of competence. With respect to its theoretical contributions, first, this study contributes to signaling theory in e-commerce by focusing on the optional functions that are more consistent with the definition of signals. Second, we contribute to the category of signals by classifying signals from the signal receivers' perspective, which efficiently depicts how signals affect sales by influencing customers' purchase decisions. Third, this study considers the role of online sellers' characteristics in the relationship between signals and sales. Practically, our findings provide implications for online sellers on how to better utilize various functions to convey signals as well as for e-commerce platforms on designing more effective supporting functions.

2 Literature Review

2.1 Signaling Theory and E-commerce

Signaling theory originates from information economics. According to Spence (1973), signals refer to the observable and manipulable individual characteristics. Signaling theory mainly focuses on how to eliminate the information asymmetry by conveying signals. Signal senders could choose whether to send signals and the types of signals to send. The observable and manipulable characteristics of signals are particularly important in the context of e-commerce platforms. In terms of observability, because asymmetric information is prevalent on e-commerce platforms, online sellers can use various functions to convey signals to eliminate the asymmetric information. In terms of manipulability, different types of signals could be autonomously chosen to convey by online sellers with different credit ratings.

Previous e-commerce research based on signaling theory explores signals from two perspectives. The first perspective focuses on categorizing signals based on certain standards. The second perspective explores the influences of signals on customers and sellers.

First, previous researchers categorize signals based on four principles. The first principle is the type of information that the signals provide. Signals can be divided into signals that directly indicate product quality (e.g., refund guarantees, product descriptions, and product certificates), signals that indirectly indicate product quality (e.g., reserve prices for auctions), signals that reveal a seller's reliability (e.g., seller ratings) (Li et al., 2009) , internal signals (e.g., return policy and privacy policy), and external signals (e.g., the anonymity and payment policy of the platform that the seller relies on) (Mavlanova et al., 2016; Choi, Ko, Medlin, & Chen, 2018). The second principle categorizes signals according to the cost of signals. Previous research indicates that incredible online sellers convey more low-cost signals than highly credible online sellers (Mavlanova, Benbunan-Fich, & Koufaris, 2012). The third principle is related to the objects to which the signals refer. Previous research divides the signals on peer-to-peer content networks into content contributors' signals (e.g., the credibility of contributors), content signals (e.g., content ratings), and the platform's signals (e.g., the credibility and legality of the platform, and the usage of rating systems for content and contributors) (Tiwana & Bush, 2014). The fourth principle is the mechanism of the signals. With this principle, signals are classified into institutional signals (e.g., credibility, rating, customer protection mechanism, return service, and warranty service), social signals (e.g., an online seller's social presence and popularity), signals that indicate the characteristics of an online seller, and signals that imply certain product features (Ou & Chan, 2014).

Second, researchers explore the influence of signals from the perspectives of customers and online sellers. From the customers' perspective, researchers mainly focus on the effects of signals on customers' cognition and behavior using experiments and surveys. The customers' cognitive and behavioral outcomes include trust (Lee, Ang, & Dubelaar, 2005; Wang, Beatty, & Foxx, 2004; Kim, Xu, & Koh, 2004; Aiken, & Boush, 2006), perceived risks (Mavlanova, Benbunan-Fich, Koufaris, & Lang, 2015), perceived seller quality (Mavlanova et al., 2016), and purchase intentions (Lee et al., 2005; Wells, Valacich, & Hess, 2011). From the online sellers' perspective, previous research concentrates on the behavior and strategy of conveying signals by analyzing objective data. For example, highly rated online sellers will convey more signals about providing flexible return policies (Bonifield, Cole, & Schultz, 2010) and more signals before customers' purchases (Mavlanova et al., 2015). Recently, researchers have investigated the impacts of various signals on online sellers' sales (Ou & Chan, 2014; Choi et al., 2018; Li, Fang, Wang, Lim, & Liang, 2015).

Unexpectedly, previous research often treats the nonoptional and unmanageable functions as signals, for example, online sellers' ratings, the number of customers that like the online seller, and the platform quality. These functions are determined by customers and platforms instead of online sellers who are the signal senders. In addition, these functions are inconsistent with the definition of signals and difficult to use to guide online sellers directly. Previous research categorizes signals from the perspective of sellers, which hardly captures how signals influence signal receivers' (i.e., customers). Thus, it is necessary to consider manipulable signals and categorize them from the perspective of signal receivers.

2.2 The Mechanism of Online Sellers' Credibility

Credibility is the public and external evaluation of an individual's attractiveness (Standifird, 2001). Previous research mainly concentrates on the direct effect of online sellers' credibility, which is generally treated as an important factor in e-commerce (Amblee & Bui, 2011; Wang, Cui, Huang, & Dai, 2016). For example, some researchers explore the impacts of credibility on customers' purchase decisions (Melnik & Alm, 2005; Rice, 2012) and evaluations of product quality (Wang et al., 2016) . Previous research indicates that credibility increases purchase intentions and positive evaluations because customers believe that highly credible online sellers are more reliable and trustworthy and intend to build long-term relationships with them (Tsai & Huang, 2009).

However, recent research indicates that credibility will interact with other variables to affect sales. For example, Li, Chhajed and Mallik (2010) suggested that online sellers with different levels of credit rating should use different product guarantee policies. Specifically, in the traditional transactional context, a credible brand will increase customers' perception that the company can meet promises better than an incredible brand (Price & Dawar, 2002). Other researchers also indicate that the refund promises of incredible sellers rarely affect customers (Moorthy & Srinivasan, 1995).

There is limited attention given to how sellers' credit rating levels interact with other variables to influence sales. In other words, online sellers with different levels of credibility could convey different types of signals to efficiently increase their sales. Exploring this is supported by theoretical and practical evidence. Theoretically, the credibility of the signal sender is a critical determinant of signals' efficiency and affects customers' trust (Price & Dawar, 2002; Tang, Hu, & Smith, 2008). Practically, customers pay attention to different information according to sellers' popularity and credibility levels. Therefore, focusing on this question provides direct guidance for the signaling strategies of online sellers.

3 Theory and Hypotheses

Based on the signaling theory and the stereotype content model, this research explores the influence of different types of signals that are conveyed by online sellers with different levels of credit rating.

3.1 Theoretical Basis and Categories of Signals

According to signaling theory (Spence, 1973), signals refer to the platform functions or mechanisms that can be leveraged by online sellers to indirectly convey information in the e-commerce context. Thus, customers can judge and evaluate online sellers according to the signals. The relationship between customers and online sellers is similar to interpersonal relationships (Fournier, 2014). The stereotype content model in psychological research provides a new perspective for exploring the influence of online sellers' signals. The stereotype content model states that individuals judge and evaluate others on two dimensions, namely, competence and warmth (Judd, James-Hawkins, Yzerbyt, & Kashima, 2005). Competence includes efficiency, skill, and expertise. Warmth includes kindness, friendliness, trustworthiness, and helpfulness. Marketing researchers indicate that the two dimensions can also be used in customers' judgments and evaluations of online sellers (Kervyn, Fiske, & Malone, 2012; Li, Chan, & Kim, 2019). Customers will judge online sellers on the two dimensions when receiving online sellers' signals. Therefore, this research categorizes online sellers' signals into two types: signals of competence and signals of warmth.

The categorization of signals is necessary and reasonable. First, we address the necessity of the categorization. Previous research mainly classifies signals based on the costs of the signals. However, according to the stereotype content model, signal receivers pay less attention to the costs of signals. In contrast, customers will divide the signals into competence and warmth to judge and evaluate the online sellers. Therefore, this category could efficiently capture the influence of signals on customers' judgments of online sellers and their purchase decisions, which further affect sales. Moreover, this categorization guides online sellers on which dimension or types of signals should they convey and focus on. Second, we address the reasonableness of the categorization. Previous researchers indicate that a function can be treated as a signal unless it meets the two requirements. One is that using the function requires corresponding costs. The other is that the costs should fulfill the single-crossing property, which refers to the costs of signals for poor performance senders are higher than those for good performance senders. Signals of competence and signals of warmth both satisfy the two requirements. To be specific, conveying signals of competence costs online sellers a lot. For example, online sellers pay fees to show an icon named "promised delivery time." Online sellers also need to compensate buyers for delivering products beyond the deadlines. Moreover, good performance online sellers have better inventory management and delivery management abilities than poor performance online sellers. Therefore, the possibility of deliveries is less for online sellers with high performance than for those with low performance. Similarly, the signals of warmth also fulfill the two requirements of signals.

Signals of competence in this research include promised delivery times and free return days. The promised delivery time means that online sellers could manipulate the delivery time based on the default time that is designed by the e-commerce platform (i.e., 72 hours). If online sellers deliver products past the promised times, they have to compensate the customers for their late deliveries. Therefore, the promised delivery time reflects the online sellers' confidence in their inventory management abilities, contractual capacities, and logistics capabilities. Free return days refer to the online sellers' promised number of days that customers can return products without any reason after receiving the products. In general, online sellers can provide more than seven free return days. The greater the number of free return days, the more confidence that online sellers have in their products' quality. Signals of warmth include online customer service functions. Customers perceive sellers' care for them through their one-to-one communications with online sellers. Online sellers could affect customer service agents' online time. Online customer service agents can respond to customers quickly if they remain online longer. Therefore, the longer the online time is, the greater the care from online sellers that is perceived by customers.

3.2 The Influence of Online Sellers' Credit Rating Levels on the Signaling Mechanism

The literature on online sellers' credibility indicates that credibility affects not only the signals' trustworthiness but also customers' attention to online sellers' information(Li et al., 2010; Price & Dawar, 2002; Moorthy & Srinivasan, 1995). Therefore, this research explores the influences of the different types of signals that are conveyed by online sellers with different levels of credit rating on sales. Credit ratings are gained by sellers' accumulated high-rating transactions. Higher credit rating levels means that the seller has gained high trust from customers and accumulates enough experience in the e-commerce platforms. We categorize sellers' creditability into three levels, namely, higher, median, and lower credit rating levels, based on their features. First, sellers with higher credit rating levels have been completely trusted by customers. Second, median-credit-rating-level sellers have some market experience but are not completely trusted by customers. Third, online sellers with lower credit rating levels include new online sellers with less experience and mature online sellers with low credibility. They gain little trust from customers.

3.2.1 The Signaling Mechanism of Online Sellers with Higher Credit Rating Levels

Customers pay more attention to whether online sellers with higher credit rating levels care for customers' need and respond immediately (Aaker, Vohs, & Mogilner, 2010). Online customer service, which is a signal of warmth, is critical to sales. This is because online customer service could increase customers' social presence through one-to-one online communications and further increase customers' purchase intentions (Gao & Li, 2019; Sun, Yang, Wang, & Zhang, 2015), which is reflected in sales. Fournier and Alvarez (2012) suggested that warmth is a critical factor for sellers' future development, while competence determines current performance. For online sellers who have already obtained customers' trust should focus on warmth if the online sellers want to expand their market shares. Bernritter, Verlegh and Smit (2016) indicated that warmth is an important factor for consumers' intentions to endorse brands online. Therefore, for online sellers with high credit rating levels, conveying signals of warmth (e.g., keeping customer service agents online all the time) increases customers' intentions to endorse the sellers and make purchases, which are reflected in sales, when compared with conveying signals of competence. We develop the two following hypotheses.

H1a: For sellers with higher credit rating levels, the available time of online customer service agents, which is a signal of warmth, positively influences sales.

H1b: For sellers with higher credit rating levels, conveying signals of warmth has a more positive effect on sales than conveying signals of competence.

3.2.2 The Signaling Mechanism of Online Sellers with Median Credit Rating Levels

Online sellers with median credit rating levels are skillful to use these functions to display their products' features and advantages, such as detailed textual descriptions, pictures, and videos. Moreover, they have some market shares and accumulate some online reviews. Therefore, customers search for information about product quality from the online sellers' descriptions and other customers' online reviews without depending on the number of promised return days, which is a signal of competence. Dimoka, Hong and Pavlou (2012) found that the uncertainty of online shopping includes the uncertainty from products and sellers. Product uncertainty can be eliminated by product descriptions and online reviews. Online sellers' uncertainty can be dispelled by sellers' promises. Xu, Cenfetelli and Aquino (2016) suggested that the influence of competence trust belief is stronger than that of integrity trust belief on customers' purchase behaviors. Therefore, customers pay more attention to service abilities (e.g., delivering products within the promised number of days) of online sellers with median credit rating levels than product quality. Because online sellers with median credit rating levels are not fully trusted by customers, conveying signals of warmth will be treated as covering up their poor competence. Aaker, Garbinsky and Vohs (2010) indicated that competence is the main reason for customers' purchases. Xu et al. (2016) suggested that customers' competence trust belief in sellers has more positive influences on purchase behaviors than benevolence trust belief. Therefore, we have two more hypotheses.

H2a: For sellers with median credit rating levels, the promised delivery time, which is a signal of competence, positively influences sales.

H2b: For sellers with median credit rating levels, conveying signals of competence has a more positive effect on sales than conveying signals of warmth.

3.2.3 The Signaling Mechanism of Online Sellers with Lower Credit Rating Levels

Customers distrust online sellers with lower credibility. Customers decide to buy products from online sellers with lower credit rating levels based on the signals of competence that are sent by these sellers. Previous research suggests that customers' trust in online sellers will affect their purchase behaviors (Xu et al., 2016) , which are reflected in sales. When lower credible online sellers promise a delivery time, they will be treated as sellers who have inventory management abilities, contractual capacities, and logistics capabilities by customers. The greater the number of free return days that online sellers with lower credit rating levels promise, the higher their confidence in the product that they provide to customers. Customers pay more attention to less credible online sellers' competence than warmth (Aaker et al., 2010; Aaker et al., 2012). Therefore, customers will not make purchase decisions based on signals of warmth that are sent by online sellers with lower levels of credit rating. Moreover, Brown (1990) indicated that salespeople from less credible companies are treated as intentional and deceptive salespeople than those from a more credible company when they use the same selling strategies. Therefore, online sellers with lower credit rating levels will be evaluated as deceptive sellers when they convey signals of warmth. The hypotheses for online sellers with lower credit rating levels are as follows:

H3a: For online sellers with lower credit rating levels, the promised delivery time, which is a signal of competence, positively influences sales.

H3b: For online sellers with lower credit rating levels, the number of free return days, which is a signal of competence, positively influences sales.

Figure 1. The screenshot of the data for signals and some control variables that were collected from Taobao.com

H3c: For online sellers with lower credit rating levels, conveying signals of competence has a more positive effect on sales than conveying signals of warmth.

4 Research Method

4.1 Data Collection

This research collects data from Taobao.com using a web crawler. The method for sample selection is searching for "women clothing" and then collecting all sellers from the search results. This research focuses on the effects of signals on sales. We include all online sellers, regardless of whether they use any functions to convey signals. Therefore, the sample in this research is representative. Customers focus more on popular and fashion products in the clothing industry (Brynjolfsson, Hu, & Simester, 2011). Online sellers display their main and popular products on the first two pages. Therefore, we randomly select five products from a seller's first two product-displaying pages. Figures 1 and 2 show the screenshot of the data that were collected from Taobao.com.

Finally, we collect 15,225 products from 3,045 online sellers who sell women's clothing. We recollect the sales data for the 15,225 products after a month and find that 10,674 products of the products are still being sold. After cleaning the data, only the data from 10,392 products can be used in the analyses.

4.2 Measurements

The dependent variable, that is, online sellers' sales, is measured by the sales in the next month. This research focuses on the influence of signals on sales instead of the variation of sales. Therefore, sales in the same month with signals are not included in our model, which is consistent with the previous research (Ou & Chan, 2014).

The independent variables are the two types of signals that are conveyed by online sellers and the online sellers' credibility levels. The credit rating level is identified by different icons, including the heart-shaped-level, the diamond-level, the royal-crown-level, and the golden crown-level. Because the numbers of online sellers with the royal-crown-level and golden-crown-level are limited, we treat these two levels at the same level, namely, the crown-level. This combination is reasonable because customers perceived royal-crown-level and golden crown-level online sellers as highly credible sellers. Therefore, the credit rating levels in this research include higher, median, and lower credit rating levels, which correspond to the heart-shaped-level, the diamond-level, and the crown-level, respectively. The numerical difference in the promised delivery times between different online sellers is

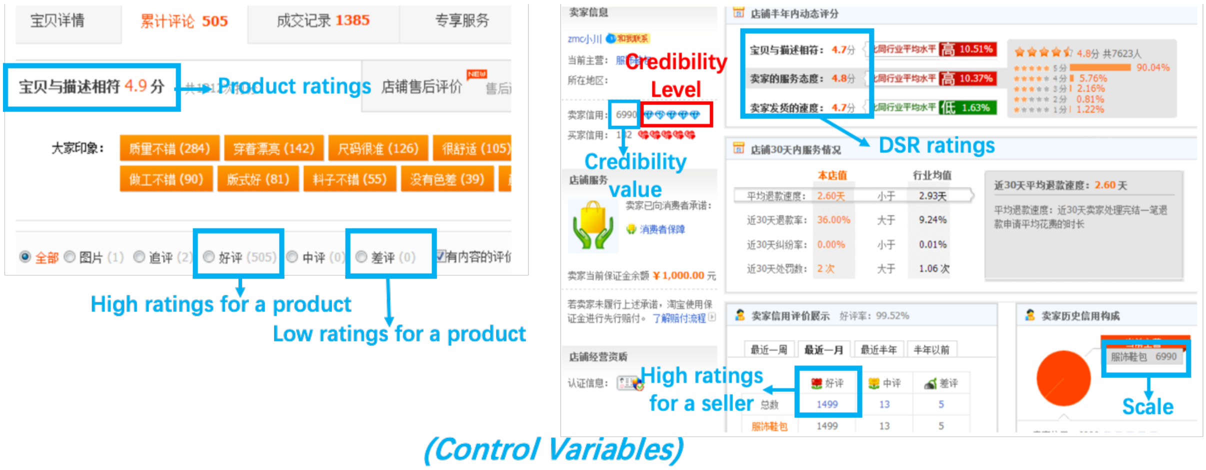

Figure 2. Screenshots of the data that were collected from Taobao.com

reflected in hours that cannot be perceived by customers. Therefore, we measure it by using a 0-1 variable that represents whether the online seller promises a delivery time. "1" represents online sellers with promised delivery times while "0" represents that they do not. For free return days, different online sellers promise different numbers of days to customers. We measure the free return days using the number of days in which an online seller promises to accept free returns. Online customer service, that is, the signal of warmth, is measured by the average time that online customer service agents remain online.

We also include other variables that may influence sales as control variables, including an online seller's credibility value, an online seller's scale, an online seller's popularity, online reviews, and product prices. The reason for including credibility values is that online sellers may have different credibility values, even if they are at the same credibility level. The popularity of an online seller and volumes of high ratings represent online sellers' growth. Sellers' growth is more meaningful than their age. For example, some online sellers who have existed for a long time sell nothing and remain offline while some new online sellers are active and then get customers' favor and high ratings. The measurements of the variables are shown in Table 1.

4.3 Analysis Model

We take the log of sales, which commonly has a high standard deviation, to ensure whether it satisfies a normal distribution. Equation (1) tests H1a and H1b by modeling how the two types of signals influence sales for sellers with high credit level. The dependent variable in Equation (1) is a seller *i*'s sales in the next month *t*+1 ($Sale_{i,t+1}$). In Equation (1), the βs are the model coefficients of interest and ϵ'_{it} is the residual error term. The influence of signals on sales for sellers with median and low credit rating levels are modeled in the same way.

5 Results

5.1 Descriptions of Variables

Detail seller rating (DSR) includes the ratings for a seller's descriptions of products, service, and logistics service. Because the difference between the three ratings is tiny, which results in multicollinearity, we simplify the DSR ratings as a 0-1 variable. "1" represents that an online seller's DSR rating is higher than the average level, while "0" refers to a lower than average level. The online sellers' different credibility levels include 1,298 crown-level sellers, 3,605 diamond-level sellers, and 5,489 heart-shaped-level sellers. The descriptions of all variables are shown in Table 2.

The correlation between variables is shown in Table 3. The correlation between DSR ratings and product ratings and that between high ratings of products and low ratings of products are high, that is, over 0.7. However, further analysis of the variance inflation factor indicates that there is no multicollinearity in the model.

Table 1
Notations and Measurements of the Variables

Concepts	Variables	Notations	Measurement
Sales	*Product sales*	$Sale_{i,t+1}$	Sales in the next month
Credibility level	An online seller's credibility level		High credibility level (crown-level), median credibility level (diamond-level), and low credibility level (heart-shaped-level)
Signals of competence	Promised delivery time	$Comp\_Delivery_{i,t}$	Whether the online seller promises a delivery time (a 0-1 variable)
	Free return days	$Comp\_FreeReturn_{i,t}$	The number of promised days for free product returns
Signals of warmth	Online customer service agents	$Warm\_CustomerService_{i,t}$	The average online time of an online sellers' customer service agents
Control variables	Credibility value	$Credibility_{i,t}$	The credibility value of an online seller
	A seller's scale	$Scale_{i,t}$	The numbers of products that an online seller sells
	Popularity	$Popularity_{i,t}$	The number of collections for an online seller
	Online reviews	$HighSellerRating_{i,t}$ $DSR_{i,t}$ $AveProductRating_{i,t}$ $PosProductRating_{i,t}$ $NegProductRating_{i,t}$	High ratings for an online seller, DSR (detail seller ratings), product ratings, higher product ratings, and lower product ratings
	Price	$Price_{i,t}$	The price of a product

Table 2
Descriptions of Variables

Variables	Mean	Standard deviation	Minimum	Max
Sales	19.20	67.52	0	777
Promised delivery time	0.536	0.499	0	1
Free return days	7.527	1.479	0	15
Online customer service agents	15.48	1.698	1.714	24
Credibility value	59805.93	385121.70	6	9126578
The scale of the online seller	181.59	748.43	4	28108
Popularity	519.51	3211.4	0	94837
High ratings for the online seller	1807	7598	6	166532
DSR ratings	0.687	0.464	0	1
Product ratings	4.764	0.161	3.5	5
High product ratings	38.99	289.35	0	14995
Low product ratings	0.465	4.725	0	284
Price	146.36	269.71	1	7580

Table 3
Correlations between Variables

Variables	1	2	3	4	5	6	7	8	9	10	11	12	
1. Sales	1												
2. Promised delivery time	−0.124	1											
3. Free return days	−0.008	0.105	1										
4. Online customer service	0.032	0.015	0.040	1									
5. Credibility value	0.311	−0.121	−0.035	0.090	1								
6. The scale of an online seller	0.116	−0.111	−0.048	0.007	0.150	1							
7. Popularity	0.286	−0.098	−0.008	0.047	0.223	0.059	1						
8. High ratings for an online seller	0.230	−0.150	−0.034	0.071	0.725	0.195	0.321	1					
9. DSR ratings	0.003	−0.029	0.028	−0.027	−0.081	−0.016	−0.049	−0.089	1				
10. Product ratings	0.043	−0.014	−0.004	−0.029	−0.053	−0.029	−0.046	−0.080	0.746	1			
11. High product ratings	0.079	−0.065	−0.003	0.010	0.129	0.030	0.507	0.232	−0.047	−0.04	1		
12. Low product ratings	0.053	−0.019	−0.006	0.023	0.083	0.018	0.384	0.162	−0.088	−0.08	0.766	1	
13. Price	−0.045	−0.053	−0.143	−0.022	−0.031	0.013	−0.03	−0.044	0.170	0.255	−0.025	−0.026	1

5.2 Hypotheses Testing Results

We test the hypotheses using multiple regressions through Stata. According to the stereotype content model (Fiske, Cuddy, Glick, & Xu, 2002), signals of competence and signals of warmth have no interactive influence. We do not consider the interaction between the two types of signals.

5.2.1 The Results of Online Sellers with Higher Credit Rating Levels

To test H1a and H1b, we analyze the data that only include crown-level online sellers. The results of models A1 and A2 of Table 4 show that online sellers with high credit rating levels that convey signals of warmth, that is, online customer service, have significantly higher sales (β=0.039, p<0.01). Therefore, H1a was supported since the longer the average online time of online customer service agents, the higher the likelihood that sellers can respond to customers immediately. Therefore, customers perceive more care and personalized service from online sellers with higher credit rating levels and have higher purchase intentions that are reflected in sales. In addition, overusing signals of competence negatively influence sales for highly credible online sellers. Specifically, the promised delivery time has a significantly negative influence on sales (β=-0.300, p<0.05)), and the promised number of free return days has an insignificant negative impact on sales (β=-0.025, p>0.05). Therefore, for highly credible online sellers, signals of warmth have more positive effects on sales than signals of competence, that is, H1b was supported.

5.2.2 The Results of Online Sellers with Median Credit Rating Levels

To test H2a and H2b, we analyze the data that only include diamond-level online sellers. The results of models B1 and B2 in Table 4 show that online sellers with median credit rating levels that use the function of promised delivery time, that is a signal of competence, will increase sales (β=0.076, p<0.05). Therefore, H2a is supported. When online sellers promise a delivery time, they will be perceived as more trustworthy because they convey implicit information about their contractual capacities and logistics capabilities. Trustworthy sellers have higher sales because trust is a critical factor for customers' purchase intentions. Signals of warmth, that is, the online customer service, have an insignificant negative effect on sales (β=-0.007, p>0.05). Therefore, signals of competence

Table 4
Results for Hypotheses Testing

Variable types	Variable	Sellers with high credibility levels (N=1,298)		Sellers with median credibility levels (N=3,605)		Sellers with low credibility levels (N= 5,489)	
		Model A1	Model A2	Model B1	Model B2	Model C1	Model C2
Constant		−2.4996	−0.9896	4.2587***	4.8687***	6.1129***	5.5438***
Control variable	Credibility value	6.88E-08	2.24E-08	2.84E-06	5.05E-06	−0.0028***	−0.0027***
	The scale of an online seller	−9.13E-05*	−1.03E-04**	−2.58E-05***	−2.58E-05***	9.04E-06	2.56E-05
	Popularity	3.00E-05***	2.85E-05***	2.82E-04**	2.83E-04**	0.0008***	0.0008***
	High ratings for an online seller	3.26E-05***	3.23E-05***	−2.46E-05	−1.83E-05	0.0019***	0.0018***
	DSR ratings	−0.1260	−0.0399	−0.0512	−0.0458	0.1906*	0.1661*
	Product ratings	1.2369	0.7735	−0.6903***	−0.6872***	−1.0705***	−1.0126***
	High product ratings	0.0003**	0.0003**	0.0013**	0.0013**	0.0338***	0.0335***
	Low product ratings	−0.0188*	−0.0178*	−0.0114	−0.0109	−0.3393***	−0.3341***
	Price	−0.0002	−0.0002	−0.0005**	−0.0004**	−9.63E-05	−4.63E-05
Signals of warmth	Online customer service (online time)		0.0386**		−0.0071		−0.0047
Signals of competence	Promised delivery time		−0.2998*		0.0763*		0.0830*
	Free return days		−0.0245		0.0018		0.0548***
Variance inflation factor		1.77	1.56	1.71	1.45	1.62	1.39
F-value		29.1	19.5	20.18	12.53	40.61	26.38
R^2		0.1918	0.2049	0.068	0.0708	0.1597	0.1638

Note: *p<0.05,**p<0.01,and ***p<0.001.

have higher positive influences on sales than signals of warmth for online sellers with median credibility levels.

5.2.3 The Results of Online Sellers with Lower Credit Rating Levels

The data that include online sellers with low credit rating levels are used to test H3a, H3b, and H3c. The results of models C1 and C2 in Table 4 indicate that online sellers with lower credit rating levels that convey signals of competence, including promised delivery time (β=0.083, p<0.05) and free return days (β=0.0548, p<0.001), have significantly higher sales. Therefore, H3a and H3b were both supported. However, signals of warmth, that is, online customer service, have an insignificant negative influence on sales (β=-0.0047, p>0.05). Therefore, H3c was supported.

5.2.4 Discussion

The empirical results show that online sellers with higher credit ratings should focus more on signals of warmth, while those with median and lower credit ratings should concentrate more on signals of competence, especially lower-credit-ratings-level sellers should pay more effort to convey signals of competence. Previous research of signaling theory indicates that the promised delivery time, the free return days, and the customer service are all generally effective signals for sellers (Ou & Chan, 2014; Li, Srinivasan, & Sun, 2009; Mavlanova et al., 2016). However, our results show that the two former signals, which are signals of competence in this research, are only effective for sellers with lower credit, and the later one, which is the signals of warmth, is critical for high-credit-ratings-level sellers. Moreover, our results are consistent with the stereotype content model (Judd et al., 2005;

Fiske et al., 2002) in that sellers should increase both their competence and warmth to gain positive evaluation from customers, which will further increase customers' purchase.

6 Conclusions

Based on signaling theory and the stereotype content model, this research categorizes signals into signals of competence and signals of warmth and explores the influence of the two signal types on sales by considering online sellers' credibility levels. We have three results. First, the signals of warmth that are conveyed by online sellers with higher credit rating levels positively influence their sales, and the positive influence is higher than that for signals of competence. Second, online sellers with median credit rating levels could promote sales by using the function of a promised delivery time, which is a signal of competence. The positive influence of signals of competence is higher than signals of warmth for online sellers with median credit rating levels. Third, online sellers with lower credit rating levels should pay more attention to signals of competence than signals of warmth.

6.1 Theoretical Implications

First, we contribute to the choice of functions as signals. Previous research mainly concentrates on the nonoptional functions as signals, which is inconsistent with the definition of a signal. According to the signaling theory (Spence, 1973), the optional and manipulable functions are more consistent with the definition of signals. Therefore, this research contributes to signaling research by focusing on the functions that better fit the definition of signals and provides more direct guidance for online sellers.

Second, this research provides a supplemental perspective for researching the influence of signals. This research categorizes signals into two types (signals of competence and signals of warmth) from the customers' perspective. This category efficiently depicts the influence of signals on customers' purchase behavior, which is finally reflected in sales. Moreover, this research provides the framework for exploring the influence of functions that are used as signals. Specifically, various functions can be treated as different types of signals. Different types of signals have different influences on customers' cognitions and behaviors (e.g., purchase behaviors, satisfaction, and intentions to recommend) and sellers' performance (e.g., sales and high ratings). Therefore, future research could classify more functions into the two types of signals and explore the influence of these functions.

Third, this research contributes to the role of online sellers' credit rating levels in the signaling mechanism. The results of this research show that the signals that are conveyed by online sellers with different credit rating levels have different influences on sales. Therefore, we provide a potential idea for exploring the influence of IT artifacts in e-commerce by considering their interactive influence with online sellers' credibility on outcomes.

6.2 Practical Implications

For online sellers, they should focus on signals of warmth or signals of competence based on their credit rating levels. Because each signal has its corresponding costs, it will cost online sellers a lot without providing benefits if they use various functions and convey all kinds of signals. Based on online sellers' characteristics, they should convey the signals that concern customers the most. Therefore, the signals can efficiently promote sales and allow online sellers to stand out from all competitors. For example, online sellers with higher credit rating levels should maintain longer online times for their customer service agents to meet customers' immediate requirements. The stereotype content model suggests that individuals with high competence, but low warmth will receive others' envy and resistance (Fiske et al., 2002). Highly credible online sellers could efficiently promote sales by conveying more signals of warmth to build long-term relationships with customers and avoid forming the perception of being indifferent sellers.

E-commerce platforms could increase their overall income by guiding online sellers on how to appropriately use the functions. On the one hand, e-commerce platforms should provide two types of functions to show the online seller's competence and warmth. On the other hand, e-commerce platforms should guide online sellers to use these functions according to sellers' characteristics. Platforms should guide the newcomer to reflect the seller's product quality and abilities. For example, the platforms could require new sellers to use the functions of the promised delivery time and free return days. In contrast, the platforms should provide high-quality chatbots for online sellers who have some experience and market shares. Because the skillful and experienced online sellers have high volumes of transactions and customer requests, they can promote sales by using the chatbots that are provided by platforms to meet all customers' requests and needs.

6.3 Limitations and Future Research

First, this research uses cross-section data to test hypotheses referring to previous research (Ou & Chan, 2014). However, cross-section data cannot explore the dynamic influence of signals. Future research could use panel data and run panel regressions to further test the results of this research. Future research could also conduct a survey from the perspective of customers to validate our results. Second, this research considers two types of signals and classifies three functions into two types of signals. Future research could consider more other functions and classify them into two types of signals. Third, this research focuses on one of the most popular industries, that is, women's clothing. Future research could explore the moderate influence of product types (e.g., search products and experience products) on the signaling mechanism. Moreover, future research could consider the service time settings in different product lines for a seller. Therefore, these specific management implications can benefit online sellers who sell different types of product and product lines.

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