Customer Information Sharing Behavior in Social Shopping Communities: A Social Capital Perspective

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CUSTOMER INFORMATION SHARING BEHAVIOR IN SOCIAL SHOPPING COMMUNITIES: A SOCIAL CAPITAL PERSPECTIVE

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Abstract

Social shopping communities provide online platform for customers to communicate their opinions and exchange product information. In this study, we explored the factors driving customer information sharing behavior in social shopping communities. We proposed and empirically tested an integrative theoretical model of customer information sharing based on social capital theory. We adopted an empirical analysis approach and collected subjective survey data and objective behavioural usage data over two months from 1,177 customers in a social shopping community. Our results generally support the theoretical model and our hypotheses. Our results show that customer information sharing is determined by social capital (i.e., indegree centrality, outdegree centrality, shared language, shared vision, and trust) factors. These results contribute significantly to the literature and provide important implications for future research and practice.

Keywords: Customer information sharing behavior, social shopping community, social media, social capital, longitudinal study
1 INTRODUCTION

Information technology has brought substantial customer relationship capabilities to organizations. For instance, customers nowadays tend to collect product information from other customers, third-party websites and eWOM networks. In recent years, we notice that social shopping communities have become a new online social platform for customers to communicate their opinions and exchange product information. Many previous studies have shown that online customer reviews significantly influence customer purchase decisions (Cheung and Thadani, 2012; Zhu and Zhang, 2010). A 2010 study by the Nielsen Company confirmed that nearly 60 percent of respondents mentioned consulting online reviews before purchasing new products/services. Because customers have increasingly come to rely on user-generated content (Chen, Xu, Whinston, 2011), it is becoming important for academics and practitioners to understand customers’ behaviors in social shopping communities.

In recent years, we have witnessed a growing number of studies that have examined the reasons why customers post their opinions, comments and reviews of products on weblogs, discussion forums, review websites, e-bulletin board systems, newsgroups and social networking sites (Cheung and Lee, 2012). Most studies tend to explain customer information sharing behavior in online communities from an individual perspective with the emphasis on cost and benefit (Henning-Thurau, Gwinner, Walsh, and Gremler, 2004). Social shopping communities are different from traditional online communities. Olbrich and Holsing (2012) suggested that social shopping communities integrate many social shopping features (i.e., recommendation list, and rating) into a virtual community of consumption. Moreover, customer participation in social shopping communities depends on interactions with and information flows among other customers. Social shopping communities allow various relationships among customers. Particularly, social shopping communities classify social ties into two types: following (outdegree centrality) and being followed (indegree centrality). The social network structure in this new form of social media is a rather unexplored social factor in this line of studies. Thus, we propose a research model of customer information sharing based on social capital.

To date, the issue of customer information sharing behavior in social shopping communities has received limited attention in the Information Systems (IS) literature. Given the enormous potential of social shopping communities as both a new vehicle for facilitating customers in the acquisition of everyday knowledge, we try to explore why customers are willing to contribute to and exchange product information with other customers in these online social platforms. Particularly, we attempt to explore how social capital affects customer information sharing in social shopping communities. Based on social capital theory, we propose that structural capital, cognitive capital, and relational capital have a direct impact on customer information sharing behavior.

Our review of prior literature revealed that most of the existing studies on information sharing have used a subjective approach to explore how and why people contribute knowledge in online communities (e.g., survey or experimental design) (Chiu, Hsu, and Wang, 2006; Oh, 2012; Sun, Fang, and Lim, 2012). In this study, we adopt a different methodological approach to explore customer information sharing behavior in a social shopping community. Specifically, we combine subjective method (i.e., survey) and objective method (panel data) to examine the underlying reasons that drive customer information sharing behavior. Moreover, previous studies on information sharing have mostly relied on cross-sectional data (Wasko and Faraj, 2005). The current study adopts a longitudinal design that empirically illustrates the causal relationship between key antecedents and customer information sharing behavior.

This paper is structured as follows. First, we present the theoretical background. Then, we provide a conceptual model of customer information sharing behavior in social shopping communities. After describing our data source, we explain the empirical strategy and present the results of our data analysis. Finally, we conclude with a discussion of the implications for theory and practice.
2 LITERATURE REVIEW

Prior literature has provided us with a rich theoretical foundation on which to build a research model that explains why customers are willing to share and exchange information in social shopping communities. In this section, we introduce the social commerce being studied and review the related literature on social capital and customer information sharing behavior.

2.1 Social Commerce

Liang and Turban (2011) defined social commerce (SC) as “a subset of e-commerce that involves using social media to assist in e-commerce transactions and activities” (p. 6). An SC website includes user ratings, reviews, recommendations, and social shopping (link of the act of online shopping store). Users in SC can collaborate online, get advice from other users, find goods, and then purchase them via the social media environment (Leitner and Grechenig 2009). Liang and Turban (2011) summarized three major attributes of social commerce: social media technologies, community interactions, and commercial activities. Social commerce has received a lot of attention for shaping emerging commercial channels in social media. Enabled by ubiquitously accessible and scalable communication techniques, social commerce has substantially changed the way consumers and retailers communicate. Forrester research (2011) predicted that the social commerce market will grow to about US$30 billion in U.S. by 2015.

In the area of social commerce, the linkage of online shopping and social networking website initiates a new form of communities: social shopping communities (Olbrich and Holsing, 2011). Social shopping communities can be defined as an online shopping platform that let consumers share, recommend, rate, and purchase products (Laudon and Traver, 2009). As such, social shopping communities have become a new online platform for customers to communicate their opinions and exchange product information. Most social shopping communities sites embed social networking functions. The social networking feature in social shopping communities is different from other social network sites (See Fig. 1 and Fig. 2). A user can subscribe to another user’s sharing by “following” him/her. The number of followings a user has indicates his/her immersion in the community and attention paid to others’ sharing. The number of followers a user has indicates his/her popularity in the community and others’ attention paid to his/her sharing.

FIGURE 1. UNDIRECTED ONLINE SOCIAL NETWORK STRUCTURE (i.e. Facebook)

FIGURE 2. DIRECTED ONLINE SOCIAL NETWORK STRUCTURE (i.e. Meilishuo)
2.2 Social Capital and Information Sharing Behavior

Social capital refers to resources embedded in a social structure that are accessed and/or mobilized in purposive action (Lin, 2001). Nahapiet and Ghoshal (1998) presented social capital as an integrative framework for understanding information sharing in organizations. They suggested that the combination and exchange of information is facilitated when (1) there are structural links or connections between individuals (structural capital), (2) individuals have the cognitive capability to understand and apply the knowledge (cognitive capital) and (3) their relationships have strong and positive characteristics (relational capital). Each of these forms of social capital constitutes the combination and exchange of knowledge between individuals within that structure. Wasko and Faraj (2005) further identified three key dimensions of social capital: cognitive, structural and relational capital and explored the roles that these dimensions play in information sharing within electronic networks of practice. Nahapiet and Ghoshal’s model focused on group-level social capital factors, whereas Wasko and Faraj’s model focused on individual-level information sharing. The results of these two studies suggest that social capital is widely recognized as exhibiting a duality: 1) at the group level, it reflects the affective nature and quality of relationships while 2) at the individual level, it facilitates a customer’s actions and reflects their access to resources (Coleman, 1990; Lin, 2001; Putnam, 1995). The fundamental proposition of social capital theory is that network ties provide access to resources (Nahapiet and Ghoshal 1998). Thus, social capital comprises both networks and assets that may be mobilized through the network (Burt 1992). In this study we focus on the unique network structure (directed social network) of social shopping communities. We assume that the directed social network structure will lead to different social capital comparing with undirected social network structure.

3 RESEARCH MODEL AND HYPOTHESES

In this study, we explore why customers share information in social shopping communities. Based on the theoretical model proposed by Nahapiet and Ghoshal (1998), we develop a series of hypotheses to examine how the three dimensions of social capital (cognitive, structure and relational) are related to customer information sharing in a social shopping community. Fig. 3 depicts our research model.

![Figure 3. Research model](image-url)
3.1 Structural Capital

Structural capital refers to connections between individuals or the structural ties created through interactions between individuals within the network (Wasko and Faraj, 2005). The fundamental proposition of social capital theory is that network ties provide access to resources. Social relations constitute information channels that reduce the amount of time and investment required to gather information. Burts (1992) indicated that these information benefits occur in three forms: 1) access, 2) timing, and 3) referrals. Access refers to receiving valuable information. It identifies the role of networks in providing an efficient information and distribution process for members of those networks. Timing refers to the ability of personal contacts to provide information sooner that it becomes available to people without such contacts. Referrals relates to those processes providing information on available opportunities to people in the networks, hence influencing the opportunity to combine and exchange knowledge.

Social network structure of social shopping communities is different from those of traditional online communities, which combine a collection of actors and the relationships (interactions) among them. In social shopping communities, a customer can choose to “follow” other customers in the community. The relationship between two members has two directions in social shopping communities: following and be followed. A focal member and his/her following and followers form a social network. Therefore, social network centrality in social shopping communities includes two types: indegree and outdegree. Indegree centrality refers to the total number of links from the other members to the focal member. Outdegree centrality refers to the total number of links from the focal member to the other members. Customers with higher indegree centrality (number of in-coming ties) can attract a larger audience because more in-coming links suggest greater popularity within the network. Customers with higher indegree centrality tend to be a “referrals” in the network. Thus, we argue that customer information sharing behavior is positively influenced by social network indegree centrality.

**H1:** Customers with higher levels of network indegree centrality will share more information.

Mossholder, Settoon, and Henagan (2005) indicated that network centrality is related to the extent of an individual’s involvement in assisting exchanges with others. A higher level of centrality within the identity confirmation network is positively related to cooperation and performance (Milton and Westphal, 2005). Moreover, an individual with higher outdegree centrality can access more resources. Based on social capital theory, an individual who gets more information from the social network is more likely to benefit the other individuals in that particular network. An individual with higher outdegree centrality tend to achieve both “access” and “timing”. Thus, we suggest that customer information sharing behavior is also positively influenced by social network outdegree centrality.

**H2:** Customers with higher levels of network outdegree centrality will share more information.

3.2 Cognitive Capital

The cognitive capital refers to the resources that create shared interpretations and meanings within a collective (Wasko and Faraj, 2005). It is an essential element of social exchanges and combination processes. Nahapiet and Ghoshal (1998) suggested that the cognitive dimension of social capital could be developed in the following ways: 1) the existence of shared language and vocabulary and 2) the sharing of collective narratives. These two elements facilitate social interaction processes. Shared language facilitates a common understanding of collective goals and the proper ways of acting in virtual communities (Tsai & Ghoshal, 1998). Previous study also indicated that shared language influence the conditions for exchanging knowledge (Chiu et al., 2006, Nahapiet and Ghoshal, 1998). Thus, we expect that customers with higher level of shared language will be more likely to share more posts within a social shopping community.

**H3:** Customers with higher level of shared language will share more information.

Shared vision refers to a bonding mechanism that helps different parts of an organization to collaborate and to combine resource. As a customer’s with higher levels of shared vision s/he can more accurately and easily assess the benefits and costs within the context of the social shopping community.
community. Therefore, we hypothesize that customers with higher level of shared vision will be more likely to share more posts within a social shopping community.

**H4: Customers with higher level of shared vision will share more information.**

### 3.3 Relational Capital

Relational capital refers to assets that are rooted in a relationship (Tsai & Ghoshal, 1998). Information sharing is facilitated by relational capital (Nahapiet and Ghoshal, 1998). Relational capital exists when individuals have a strong identification with the collective because they are more willing to help each other when everyone is part of the accepted collective (Leana and Van Buren, 1999). In this study, we examine the relational capital using trust and identification. Mcknight et al. (1998) defined trust as the extent to which one believes in and is willing to depend on another party. Trust has been recognized as an important factor in IS research on business relationships, knowledge sharing, and e-commerce (Ridings, Gefen, and Atrinze, 2002). Chiu et al. (2006) indicated that trust is important in virtual communities for knowledge sharing. Therefore, we hypothesize that customers with higher level of trust will be more likely to share more posts in a social shopping community.

**H5: Customers with higher level of trust will share more information.**

Identification is an internalized social norm that is conceived as a benefit to individuals engaging in social exchanges (Perugini, Gallucci, and Presaghi, 2003). Previous research has found that people who share knowledge confirm identification in online communities (Wasko, and Faraj, 2005), and it is the motivation that drives them to participate and share. Thus, we believe that a customer has received the identification from other members in the community will be more likely to share more posts within the community.

**H6: Customers with higher level of identification will share more information.**

### 4 RESEARCH METHOD

In this section, we present our data collection method and operationalization of constructs for this study.

#### 4.1 Research Setting

The data for this study was collected from Meilishuo (www.meilishuo.com), a popular online social shopping community in China. Meilishuo provides an online platform where users can share their favorite products and interact with others. The information sharing focuses on fashion and lifestyle products. Launched in Nov 2009, Meilishuo is one of the most popular websites in mainland of China. Meilishuo has conventional direct sharing feature, and users can post their favorite products by providing pictures and brief descriptions in the community. They can include detailed information about a specific product, such as product price, tags, and information about online shops that sell the product. Purchases can be made through following a link to an online store. In addition to direct sharing features, users can integrate many social sharing features into their profiles such as “liking” list, and users can show their “like” to other users’ posts. This function can be used to collect products or as recommendations for other users. The platform provides social networking features, where users can choose to “follow” other customers in the community. In this sense, each customer has his/her own social network in the community and is regarded as an ego actor in the social network. This platform provides rich data that allow us to investigate how social capital affects information sharing behavior in social shopping communities.

#### 4.2 Data Collection Procedure

We conducted a survey and collected individual usage information during a three-month period (November 2012 through January 2013). Our research model was assessed in a longitudinal setting in which customers who shared information in the social shopping community completed an online
survey questionnaire at time t (November 2012). In addition, their actual usage data were observed at time t. Two months later (time t+1), their actual use behavior (e.g., information sharing in the social shopping community) was collected directly from the social shopping community (See Fig. 4). A total of 1177 completed online questionnaires were obtained. Survey data and actual usage data of the website served as the input for the current analysis of customer information sharing behavior in social shopping communities.

![Diagram showing data collection process]

**Figure 4. Time windows**

### 4.3 Operationalization of Constructs

We operationalize the constructs included in the research model as follows.

**Indegree Centrality (time t) (IND).** A customer may follow other customers within the social shopping community. The relationship between the two customers is established when one follows another. Each customer in the social shopping community has an “ego” social network and a focal customer with his/her followings and followers form a social network. Indegree centrality of a social network is the number of ties from other customers to a focal customer. In this study, the independent variable, indegree centrality, is operationalized as the total number of followers.

**Outdegree Centrality (time t) (OUD).** Similar to indegree centrality, outdegree centrality of a social network refers to the number of ties from a focal customer to other customers. In this study, the independent variable, outdegree centrality, is operationalized as the total number of followings.

**Customer Information Sharing Behavior (time t+1) (CISB).** The dependent variable, customer information sharing behaviour, is operationalized as the total number a customer has posted in the community until time t+1 (January 2013).

The measures of the constructs (i.e. shared language, shared vision, trust, and identification) in this study were borrowed from the existing scales that prior literature has shown to be reliable and valid. The scales measuring the shared language, shared vision, trust, and identification were adapted from Chiu et al. (2006). The items of the constructs are listed in Table 1. All items with minor wording modifications were applied to fit the research context. All constructs were measured using multi-item perceptual scales and were carried out by a seven-point Likert scale, ranging from strongly disagree (1) to strongly agree (7).
5. DATA ANALYSIS

5.1 Sample Characteristics

A total of 1177 usable questionnaires were collected in this study. Among the 1177 respondents, 91.3% was female and 8.7% was male. A majority of our respondents (81.3%) were aged between 20 and 29. 74.5% of our respondents had an education level of the university or above.

5.2 Reliability and Validity of the Measurement

Reliability and validity tests were conducted for measurement model verification. The reliability was tested using Cronbach’s α and composite reliability (CR). Cronbach’s α and CR should be at least 0.70. It implies that a construct retains internal consistency. Results are shown in Table 1. All two conditions of reliability were satisfied in our data sample by having the CRs ranging from 0.91 to 0.96, and the Cronbach’s α from 0.85 to 0.95.

The convergent validity and discriminant validity of the constructs in the model were examined. Convergent validity was tested using three criteria of all constructs: (1) the composite reliability (CR) should be at least 0.70 (Chin, 1998), (2) the average variance extracted (AVE) should be at least 0.50
(Fornell & Larcker, 1987), and (3) all item loadings should be greater than 0.70. Results of analysis are shown in Table 1. All three conditions of convergent validity were satisfied in data sample by having the CRs ranging from 0.91 to 0.96, and the AVEs from 0.77 to 0.84. The item loadings were all higher than the 0.70 benchmark.

Discriminant validity is the degree to which the measures of two constructs were empirically distinct. Discriminant validity between constructs can be verified if the square root of the AVE for each construct was greater than the correlation between constructs (Fornell & Larcker, 1987). As shown in Table 2, the square root of AVE for each construct was greater than the correlations between the constructs and all other constructs. Therefore, the results suggested adequate discriminant validity.

<table>
<thead>
<tr>
<th></th>
<th>SL</th>
<th>SV</th>
<th>TRU</th>
<th>IDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>SL</td>
<td>0.88</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>SV</td>
<td>0.67</td>
<td>0.92</td>
<td></td>
<td></td>
</tr>
<tr>
<td>TRU</td>
<td>0.59</td>
<td>0.61</td>
<td>0.91</td>
<td></td>
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<tr>
<td>IDE</td>
<td>0.69</td>
<td>0.69</td>
<td>0.54</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Table 2. Discriminant validity (Diagonal elements are square roots of the average variance extracted)

### 5.3 Binomial Regression Analysis

Table 3 summarizes the descriptive statistics (mean, standard deviation, minimum and maximum) for the variables used and correlations among variables. Customer information sharing behavior is represented by a count variable because it adds together all of the posts that are added to a post list. Poisson regression and negative binomial regression are often used to analyse count data. A Poisson regression model makes a very restrictive assumption that the mean of the dependent variable equals the variance (Cohen, Cohen, West, Aiken, 2003). If the variance is greater than the mean, the data are said to be over-dispersed, which can lead to the inflation of the goodness of fit chi-square test and the overestimation of predictor significance (Cohen, Cohen, West, Aiken, 2003). One approach to over-dispersion is to use a negative binomial regression model (Cohen, Cohen, West, Aiken, 2003). For customer information sharing behavior, the variances are greater than the means (variance of CISB = 1576255.14, mean of CISB = 186.50). The data are over-dispersed. Therefore, in this study, we adopted a negative binomial regression (using SPSS) to test the hypothesized effects.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>IND</th>
<th>OUD</th>
<th>SL</th>
<th>SV</th>
<th>TRU</th>
<th>IDE</th>
<th>CISB</th>
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<tr>
<td>IND</td>
<td>2055.32</td>
<td>22126.60</td>
<td>0</td>
<td>574509</td>
<td>1.00</td>
<td>0.03</td>
<td>0.88</td>
<td>0.01</td>
<td>0.54</td>
<td>0.89</td>
<td>1.00</td>
</tr>
<tr>
<td>OUD</td>
<td>54.14</td>
<td>594.33</td>
<td>0</td>
<td>17458</td>
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<td>0.01</td>
<td>0.67</td>
<td>0.02</td>
<td>0.59</td>
<td>0.61</td>
<td>0.91</td>
</tr>
<tr>
<td>SL</td>
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<td>7</td>
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<td>0.61</td>
<td>0.91</td>
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<td>0.61</td>
<td>0.91</td>
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<tr>
<td>CISB</td>
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<td>21202</td>
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<td>0.06</td>
<td>0.07</td>
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</tr>
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</table>

Table 3. Descriptive statistics and correlations

The results were presented in Table 4. We summarized the Omnibus test results, coefficients, Wald statistic, associated degrees of freedom and significance level of each of the predictors. A negative binomial regression analysis was performed with customer information sharing behaviour as dependent variables and reputation, enjoyment of helping, indegree centrality, outdegree centrality, customer tenure, customer expertise and commitment as independent variables. The Omnibus test revealed that the full model significantly predicts customer information sharing behavior (Likelihood Ratio Chi-Square = 1379.35, df = 6, p < 0.0001). The results support most of our hypotheses. To be specific, with an exception of the relationship between enjoyment of helping and customer information sharing behavior, all of the other hypotheses are statistically significant.

All the three perspectives of social capital are found significant in determining customer information sharing behavior. From a structural capital perspective, indegree centrality exerts a significant positive effect on customer information sharing behavior ($\beta = 0.001$, p < 0.05), which supports H1. Outdegree centrality is significantly related to customer information sharing behavior ($\beta = 0.002$, p < 0.05),
which supports H2. From a cognitive capital perspective, shared language has a positive effect on customer information sharing behavior ($\beta = 1.620$, $p < 0.0001$), which supports H3. Moreover, shared vision has a significant effect on customer information sharing behavior ($\beta = 0.638$, $p < 0.05$), which supports H4. From a relational capital perspective, trust shows a significant positive effect on customer information sharing behavior ($\beta = 0.556$, $p < 0.0001$), which supports H5. Surprisingly, our results indicate that identification does not exhibit any significant effect on customer information sharing behavior.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Customer Information Sharing Behavior</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>β</strong> df Sig.</td>
<td></td>
</tr>
<tr>
<td>Structural Capital H1 Indegree Centrality</td>
<td>0.001*** 1 .031</td>
</tr>
<tr>
<td>Structural Capital H2 Outdegree Centrality</td>
<td>0.002*** 1 .038</td>
</tr>
<tr>
<td>Cognitive Capital H3 Shared Language</td>
<td>1.620*** 1 .000</td>
</tr>
<tr>
<td>Cognitive Capital H4 Shared Vision</td>
<td>0.638*** 1 .017</td>
</tr>
<tr>
<td>Relational Capital H5 Trust</td>
<td>0.556*** 1 .000</td>
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<tr>
<td>Relational Capital H6 Identification</td>
<td>0.090 1 .614</td>
</tr>
</tbody>
</table>

Table 4. Results of binomial regression analysis

6 DISCUSSION AND CONCLUSIONS

The main purpose of this study is to explore the factors driving customer information sharing behavior in social shopping communities. We adopt an empirical analysis approach and collected subjective survey data and objective behavioral data from a real social shopping community. Our results generally support the theoretical model and our hypotheses.

6.1 General Discussion

Our results show that social capital plays an important role in explaining customer information sharing. All three social capital dimensions (structural, cognitive and relational) have a significant impact on customer information sharing. For instance, our results show that customers who connect to a large number of other customers (i.e., indegree centrality and outdegree centrality) are more likely to share information. Shared language and shared vision are also important predictors of customer information sharing. Finally, the relational dimension of social capital, trust, has a significant impact on customer information sharing. These findings support our argument that social capital factors play important roles in customer information sharing behavior in the context of social shopping communities. However, identification does not show any significant effect on customer information sharing behavior. The result is similar to Chiu et al.’s findings (2006) that identification is not a significant predictor of knowledge sharing. Their explanation is that identification may have indirect effects on knowledge sharing via trust. One possible explanation may be that members are willing to share information due to close and frequent interaction among members, without necessarily identifying with other members in the social shopping community.

In interpreting the results of this study, a number of limitations should be taken into consideration. First, given that our data was collected from a social shopping community, our samples were primarily female. Thus, a gender bias certainly exists. Future studies should test our model with a gender neutral data sample. Second, both information sharing and seeking behaviors are indispensable parts of virtual communities. Nonnecke et al. (2006) indicated that only focus on one aspect of community members’ behavior will lead to inappropriate design of virtual communities. Future studies will consider both information sharing and seeking behaviors.
6.2 Research Implications

This study contributes to the information sharing literature in several ways. First, existing information sharing studies focus on traditional online communities, whereas this study enriches the literature by examining customer information sharing behavior in a new social media arena; specifically, social shopping communities. This study provides strong empirical support for the information sharing model, which indicates that social capital has a significant effect on customer information sharing behavior. Second, our study extends the existing research in terms of the method we adopted for this investigation. In this study, we combined two methods: subjective method (i.e., survey) and objective method (panel data) and identified the underlying motives behind customer information sharing behavior in social shopping communities. Finally, we empirically illustrate the influence of social capital in a longitudinal setting. To the best of our knowledge, this study is one of the first studies to demonstrate the longitudinal implications of customer information sharing in the context of social shopping communities.

6.3 Managerial Implications

The findings of this study are also useful to social shopping communities, which represent a new type of social media platform. First, from a structural perspective, managers should focus on network structure development to enhance information exchange through social network structure. The following-follower feature (network structure) has played an important role in the continuance of customer information sharing. Both outdegree centrality and indegree centrality have an important impact on customer information sharing in social shopping communities. As such, the more posts a customer can access from his/her following, the higher the chance that he/she will contribute. Thus, community designers should add features that encourage members to continue to follow others. Such as, community might add “People you may interest in” or “Your Friends are also following this person” functions to expand members’ followings. From a cognitive perspective, shared language facilitates customers’ ability to gain access to people and information. It provides a way in which customer build common vocabulary in their domains. Shared language and shared vision could help share ideas and enhance the efficiency of communication. Managers should pay attention on the information content of customers in their practices. Manager should provide a tutorial to new customers when they registered as new member. From a relational perspective, managers can facilitate trust relationships among customers by encouraging customers to disclose personal information and browse other customers’ information to familiar with them.

6.4 Conclusion

In this study, we use social capital theories to explain how social capital affects customer information sharing behavior in social shopping communities. Unlike other studies on information sharing, we extend the existing framework by introducing the network features of social shopping communities into our investigation. In addition, we empirically test our research model and hypotheses using combined method (survey, and panel data) in a longitudinal setting. We hope that this empirical analysis approach will bring new insights to researchers with a strong interest in understanding customer information sharing behavior in social media.

References


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