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The Activity Evaluation Model and Sustainable Interactive Management Strategies of Online User Innovation Community

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Abstract: With the development of social network, online user innovation communities (OUICs) become an important source where many companies gather valuable information for innovation development of their products or services. Activity is an important measure of whether an OUIC is developing normally. Therefore, it is crucial to understand what factors affect the activity of an OUIC, and how to increase it, so as to gain more insights from customers. So far, there has been scarce studies that examined activity in OUICs. To this end, first, we propose an evaluation model to assess activity of OUICs, and then we take two smartphone online communities as an example, namely Xiaomi community and Samsung community, to calculate and compare their activities. The result shows that the activity in Xiaomi community is higher than Samsung community during a certain period of time. Second, it is suggested that companies can improve activity of OUICs through increasing interaction in communities. We make an attempt to explore the factors that impact interaction in OUICs by conducting a questionnaire survey to OUIC users. It is found that environmental factors, information factors, personal factors, and trust factors mostly have a significant effect on interaction of OUICs. Finally, we put forward specific management strategies for improving the interaction of OUICs, according to our research findings.

Keywords: online user innovation community; activity evaluation; interactive management strategy

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1. Introduction

Online communities nowadays are increasingly popular, thus having a huge impact on our life. They have become one of the most popular forms of online services globally [1]. Consequently, a large number of studies focused on this area in the literature (e.g., [2–4]). Online communities have very broad applications, with their fast development, such as online social networking, electronic business, online education, and open innovation. Open innovation is an innovation paradigm shift from a closed to an open model, and it is becoming more and more important for companies to adopt outside knowledge [5]. The innovation paradigm can better collect ideas from all kinds of people, including their customers or potential customers, and usually with lower cost and higher performance on product/service innovation [6]. It is important for many companies to implement open innovation, despite the difficulties associated with managing these activities [7]. Therefore, some researchers' focus on purely internal R&D activities have shifted to open innovation [8]. There is one particular stream of literature that aims to examine open innovation in online communities, namely, online user innovation communities (OUICs), because companies began to realize how much business value they can derive from such kinds of communities (e.g., [9–11]).

OUICs are electronic social environments that allow globally distributed customers to share their expertise and knowledge with one another and organizations, by commenting on existing products and services, and proposing new innovations [12]. Companies can identify valuable information generated by their users and make decisions on innovation accordingly. Here, users in OUICs refer to their members, who registered and participated in activities in the community. Users can post, comment on, and vote for new ideas about innovation in OUICs [13]. Therefore, companies can use this particular social media technology for open innovation by crowdsourcing creative ideas about new products, services, and processes [13].

It is of great significance for companies to do product or service innovation using social media technology in the Internet era [14]. In this context, user-oriented innovation in online community has become a key to sustain companies' competitiveness in market. Users in OUICs support each other in solving problems and generating new product ideas. Therefore, OUICs can be a valuable source of innovation [15]. Up to date, most of the relevant studies focused on how exactly those online communities influenced companies' innovation process, how to identify valuable and usable ideas from online users, and user behavior in OUICs (e.g., [14,16,17]). For example, it is indicated that a contributor's prior participation and prior implementation rate, as well as the idea's popularity, length, and supporting evidence, have influences on the innovation idea's implementation likelihood [14]. Active users in OUICs are likely to generate ideas that companies find valuable enough to implement, but are unlikely to repeat their early success once some of their ideas are implemented [16]. Another finding is that users in OUICs not only overestimate the potential of their ideas, but also underestimate the cost of implementing them. As a result, the number of user-contributed ideas decreases over time [17].

However, relatively little attention has been paid on assessing the activity of OUICs and exploring their impact factors, which also brings significant insights for companies to better understand their customers' needs, and as a result, produce better-customized products. Here, we refer to activity as the participation degree of users in online communities. Activity is often an important factor in measuring whether an online community operates well [18], and long-term participation is important for the survival of a community [19]. Only when the activity of an OUIC is high, will users be more likely to exchange information and experiences with each other, and then present innovative ideas in a promising way. It is suggested that active users in an OUIC are contributors of high-potential ideas, while those with low-potential ideas eventually become inactive [14]. From the perspective of users, they can also get benefits from OUICs. Users actively interact by commenting on others' ideas, generally perceive more benefits, and tend to feel a greater sense of community membership [20]. OUICs are also a social networking platform where users can make friends as they can communicate with others freely. In addition, users can find needed information provided by other active users. Further, users may even reap benefits of their own idea implementation. To fill the gap in the literature, we aim to address the following three major research questions: (1) How to evaluate the activity of an OUIC? Specifically, how to find some indicators and build a mathematical model to access the activity in an OUIC during a certain of time? (2) What are the impact factors of activity in OUICs? (3) How to improve the activity?

The rest of the paper will be organized as follows. Section 2 reviews the related work on user innovation community, activity of community, and interaction in community. In Section 3, we propose an activity evaluation model and calculate activities of two OUICs. Section 4 presents impact factors of interaction in OUICs through an empirical analysis, followed by sustainable interactive management strategies to improve and maintain the activity in Section 5. Finally, we discuss major findings and their research and practical implications, as well as limitations of this study and future research opportunities in Section 6.

2. Literature Review

With the development of information and communication technology, social media marketing becomes very critical for both customers and companies. Social media marketing is an interdisciplinary and cross-functional concept that uses social media (often in combination with other communications channels) to achieve organizational goals by creating value for stakeholders [21] (p. 123). Companies are increasingly investing in social media to foster relationships and interact with customers [22]. Meanwhile, advances in internet, collaboration tools, and web 2.0 technologies have been the key driver of open innovation, allowing companies to collaborate more easily and at low cost with a large number of customers [23]. Online communities have been used as a tool to facilitate open innovation. Prior researchers examined the applications of social media for open innovation and evaluated the motivation, implementation, impacts, and challenges encountered that in the innovation process [23]. There are many perspectives to study open innovation, such as the user perspective, the supplier perspective, the process perspective, the tool perspective, the cultural perspective, etc. [24]. User innovation is one of open innovation's most-researched fields, and also plays a very important role in online community research. Companies that effectively build strong OUICs can enhance internal research and development activities by allowing customers to identify new sources of innovation at lower costs [12]. Increasing numbers of researchers have thus contributed in this research area. There have been extensive studies on online communities from a variety of perspectives in recent years. In this paper, we break down our focused literature into two streams. The first stream is regarding how and why users do innovation activity in OUICs, and their influences on companies. We also try to review literature that examines the activity of online communities and interaction in online communities.

2.1. Online User Innovation Community

There has been research to try to explore if and how members of online communities can be integrated into new product development [10]. In order to improve work efficiency of user innovation community, they proposed the term "community-based innovation", and four steps, including determination of user indicators, community identification, virtual interaction design, and user access and participation. One of their major findings is that community members are capable and willing to contribute to virtual co-development. Fun-factor and intrinsic stimuli proved to be more important than monetary incentives for motivating potential participation in communities. The motivation of users participating voluntarily in product innovation activities (or value co-creation) in such online communities also attracted researchers' attention [25]. They developed and tested a conceptual model that explained users' benefits for doing so. Customers' participation in online communities is not because of "altruistic" or "citizenship" motives, but to attain significant benefits from such participation (i.e., enhanced product knowledge, communication with other knowledgeable customers, enhanced reputation, and cognitive stimulation and enjoyment). They also suggested that companies should design online communities which maximize potential benefits to customers for their participation. Parmentier and Mangematin [26] studied the influence of online communities on co-innovation between companies and customers. Co-innovation with OUICs requires companies to successfully manage the relationships between company and community, so as to improve their products or services. Three elements have been found in the transformation of innovation management: opening and redefining firm boundaries; opening of products and services to community input and reducing property rights; and reshaping organization and product identities. The extent to which companies are able to derive business value form OUICs has also been examined [13]. Specifically, they conceptualized two OUIC-enabled capabilities and found that one of them, which is implementation capability, increases company value. Li, Kankanhalli [14] examined the likelihood of innovation idea implementation based on characteristics of submitted idea and its presentation, as well as characteristics of its contributor. It is found that the contributor's prior participation and prior implementation rate, idea's popularity, length, and supporting evidence, can influence the innovation idea's implementation likelihood. Another research finding regarding idea implementation in OUICs is that users tend to significantly underestimate the costs to the company for implementing their ideas, but overestimate the potential of their ideas in the initial stages of the crowdsourcing process [17]. They also concluded that companies can enhance the efficiency of idea markets by providing more detailed information regarding its implementation costs. To better understand typical research questions in this area, we summarized the abovementioned studies in Table 1.

Table 1. Typical Research Questions about Online User Innovation Communities (OUICs).

Research Questions	Author
How to integrate users of OUIC into product innovation?	Füller et al., 2006 [10]
What is users' motivation for participation in OUIC?	Nambisan & Baron, 2009 [25]
What are the key elements of innovation management in OUICs?	Parmentier & Mangematin, 2014 [26]
What is the cost structure of idea implementation? Why does the number of contributed ideas decrease over time?	Huang et al., 2014 [17]
Which OUIC-enabled capabilities increase company value?	Dong & Wu, 2015 [13]
What kind of ideas contributed by users are more likely to be implemented by companies?	Li et al., 2016 [14]

From the above research literature, we found that most research focused on the users' motivation of participating in OUICs, user innovation value, how to promote users to carry out innovation implementation, and the cost of idea implementation. However, there has been scarce research assessing the activity and how to maintain activity of OUICs. If companies cannot maintain a certain activity of an OUIC, that is, innovative users are not willing to exchange technical information and their experiences with each other, then OUICs lose their value to the companies. Therefore, there is great practical significance and theoretical value in how to evaluate and maintain the activity of OUICs.

2.2. *Activity and Interaction in Online Communities*

In online communities, activity is an important indicator to measure the status of website operations. Scellato and Mascolo [27] presented a measurement study of user activity on a popular online location-based social network with hundreds of thousands of users. They focused on three important indicators of user activity: adding online friends, making check-ins, and visiting new places, which provide researchers one of the first characterizations of user activity on fast-rising location-based social services. They found that the difference in the distribution of friends and check-ins/places may be motivated by physical constraints that do not allow users to steadily visit very large numbers of new places, while online friends can be added at virtually no cost. To examine user activity, Kalaitzakis, Papadakis [28] studied MySpace, and described the formation of a community according to two well-established communities. They collected a large number of user profiles in order to characterize user activity. Their research suggested that user activity was diminishing, while the number of new users joining the network remains high. It is found that the average activity of a user is linearly correlated with the total number of actions performed by the user on the web [29]. They also studied some statistical properties of human activities in the web, and found a main difference, which is given by the range of interaction between users. There are three kinds of interaction according to their research: users are totally independent, communications are restricted between two users, and each user's action is dependent on the actions performed by a group of other users. Further, Wang, Guan [30] carried out research on a type of user with the highest activity for improving the quality of Sina Weibo user experience. One of their interesting research findings is that users who have around 300 followers are the most active users on Sina Weibo.

Interaction is a very common user behavior, and considered as a major characteristic of an online community [31]. A large amount of information is provided by user interactions. Interaction characteristics were defined as information exchange among community members and between community members and host of community. They are measured by activity in exchanging information and interpersonal exchanges, speed of inquiry and response, and exchanges between host and members [31]. The interaction of the online community has three characteristics, which are product information sharing, community interactivity, and community engagement [32]. It can also be categorized into three types, including the interaction between members, the interaction between members and organizers, and the interaction between organizers and community [33]. The interaction between users and community managers is described as customer participation and joint problem solving [34]. It is found that these two dimensions have a clear positive correlation with customer information quality. The engagement of users in the community is regarded as an interactive process, and it is thought consumer engagement can enhance consumer loyalty, satisfaction, empowerment, connection, emotional bonding, trust, and commitment [35].

To the best of our knowledge, there has been scarce research focused on activity evaluation in OUICs, which shows a great opportunity to explore in this area. In addition, previous research regarding the interaction of online community mostly focused on the community interaction itself, the interaction of consumer in the community, and the relation of perceived trust. However, there are few studies on the interactive management strategy for maintaining or improving the activity in user innovation community. Therefore, we aim to fill the gap in the literature in this work.

3. Activity Evaluation Model

OUICs in smartphone industry, which has a large number of user resources, are developing rapidly, due to the prevalence of mobile internet technology [36]. Therefore, we took OUICs in smartphone industries as an example. Specifically, we chose Xiaomi community and Samsung community as examples to conduct our research. Xiaomi Inc. is a Chinese electronics company and makes smartphones, mobile apps, laptops, and related electronics. Although Xiaomi was built in 2010, it already became China's largest smartphone company in 2014, and the world's fourth largest smartphone manufacturer in Q1 of 2018, according to International Data Corporation's Worldwide Quarterly Mobile Phone Tracker [37]. As one of its strong competitors in the smartphone industry, Samsung has long been a giant company for years. These two companies both have their own online user innovation communities, namely Xiaomi community and Samsung community. Based on their large numbers of customers, they both have sufficient and active users. Therefore, we can use them to do a fair comparison. Note that all data were collected on their Chinese websites. To create an activity evaluation model, evaluation indicators were extracted from OUICs. We set a probability level of community activity and established an activity score model. After that, we introduced a case study to verify the presented model. To this end, users ID in Xiaomi community and Samsung community, number of posts, and their posting time were collected automatically by using a web crawler. We then calculated and compared the activity of these two communities.

3.1. Selection and Definition of Activity Indicators

As mentioned above, activity is an important measure to indicate the operating conditions of an online community. We used frequency of user's participation in community to measure the activity. We extracted five indicators all together, including the change rate of active user numbers, defined as $Hy(\Delta)$, the change rate of original posts, defined as $Yc(\Delta)$, the change rate of community news, defined as $Dt(\Delta)$, the change rate of user numbers participating in community activities, defined as $Hd(\Delta)$, and the change rate of discussion topic numbers, defined as $Th(\Delta)$. These activity indicators are defined specifically as follows:

As shown in Equation (1), $Hy(\Delta)$ refers to the change of active user numbers in a community in a certain period of time:

$$Hy(\Delta) = \frac{Hy(i) - Hy(j)}{i - j} = Hy' \quad (1)$$

where i and j represent the end and begin time of the certain time period, respectively. If the number of active users in the community increases in a certain amount of time, then the community's activity increases as well. Active users were defined as the users who posted more than two posts during the time interval Δt. Similarly, the change rate of original posts of community, the change rate of community news, the change rate of user numbers participating in community activities, and the change rate of discussion topic numbers were defined specifically as the following equations, respectively:

$$Yc(\Delta) = \frac{Yc(i) - Yc(j)}{i - j} = Yc', \tag{2}$$

$$Dt(\Delta) = \frac{Dt(i) - Dt(j)}{i - j} = Dt', \tag{3}$$

$$Hd(\Delta) = \frac{Hd(i) - Hd(j)}{i - j} = Hd', \tag{4}$$

$$Th(\Delta) = \frac{Th(i) - Th(j)}{i - j} = Th'. \tag{5}$$

Hy', Yc', Dt', Hd', and Th' are the five key factors in the model. They were defined as the basis for evaluating activity in OUICs. If these five factors increase, the activity of the community would also increase. The change rates can be further quantified as score G and probability p. G represents the activity score while p indicates the probability of an active community. The five factors were defined uniformly as the five eigenvectors of the general factor Y, as shown in Equation (6):

$$Y = \left(Hy', Yc', Dt', Hd', Th'\right). \tag{6}$$

Accordingly, as shown in Equation (7), the first order partial derivatives and the second order partial derivatives of Y, over time t, can be expressed as

$$Y' = \frac{dY}{dt}, Y'' = \frac{d^2Y}{dt^2}. \tag{7}$$

3.2. Activity Evaluation Model

In order to clearly differentiate activity levels of different OUICs and show hierarchical relationships among them, we established the corresponding criteria for the level of community activity. If the probability p calculated by the activity evaluation model is larger than a threshold probability, or the score G is larger than the threshold score, we then consider the community tends to be active. By contrast, if the probability p is smaller than the threshold probability, or the score G is below the threshold score, we consider the community tends to be inactive. If p is larger than 90%, the community is most likely to be active. If p is somewhere between 70~90%, the community is very likely to be an active community. When the p value continues to decline, the possibility of a community to be inactive gets larger. In the case of p value below 20%, the activity of the community is very low. We believe the users in the community barely participate in any activity.

We then calculated the second order derivatives of the five factors over time t: $Hy'' = \frac{Hy(i) - Hy(j)}{t}$, $Yc'' = \frac{Yc(i) - Yc(j)}{t}$, $Dt'' = \frac{Dt(i) - Dt(j)}{t}$, $Hd'' = \frac{Hd(i)-Hd(j)}{t}$, $Th'' = \frac{Th(i)-Th(j)}{t}$. The decision algorithm of an active community is shown in Equation (8):

$$\Delta = \begin{cases} 0, & Y'' = 0 \\ \sum \frac{Y'}{Y''}, & Y'' \neq 0 \end{cases}. \tag{8}$$

There are three kinds of results of Equation (8): $G = 0$, $G < 0$, and $G > 0$. If G equals to zero, it means that the community is about to be active or inactive. When G is larger or smaller than zero, the probability of the community being active would increase or decrease respectively.

To better differentiate activities in various communities, we defined sine value of angles between the change characteristic curves of user participation in community, and the X-axis as activity score of the community at time t, namely, $H(t) = \sin\theta$. $H(t)$ indicates the degree of activity of user participation in an OUIC. The higher the $H(t)$ value, the greater the sum of change rates of the five factors in the community. The probability model of an active community is given in Equation (9).

$$P(t) = \sin\theta \times 100\% \tag{9}$$

$P(t)$ indicates the probability that a community is considered as an active community at time t. The community with low activity scores of less than 0.1 is an inactive community. The community with the activity score between 0.1 and 0.4 is a low active community. The scores ranged from 0.4 to 0.6 mean that the communities are medium active. The scores between 0.6 and 0.8 indicating high activity, the users of these communities have high participation and activity. The community with a score higher than 0.8 is very active, which means the users are extremely active in the community.

We can calculate the activity score, $H(t)$, by knowing Hy, Yc, Dt, Hd, Th, i, and Δt. The score was taken as an initial input of the active community probability level model algorithm, and the output was the probability of an active community.

We calculated the probability of each community as an active community, and combined the probability level criterion of the active community to the corresponding activity level. Thus, on the basis of this model, we can evaluate the activity of many smartphone OUICs, like HUAWEI, Xiaomi, Meizu, Samsung, Coolpad, Vivo, Oppo, Lenovo community, and so on. In addition, we can extend this approach to OUICs in other industries, and evaluate and compare their activities.

3.3. Case Study

We took Xiaomi community and Samsung community as an example and evaluated their activities. Unlike ordinary online communities, users in these two communities provide innovative ideas, and actively interact with each other and the company. In addition, they both have a larger number of users, thus, we chose them to conduct our research and do a fair comparison. Figures 1 and 2 [39] are two screenshots, and give examples of the two communities, respectively. We can see that their designs are actually very similar.

Figure 1. A screenshot of Xiaomi community.

Figure 2. A screenshot of Samsung community.

First, we needed to collect data from these two communities. It is suggested that one day might be appropriate for collecting data from a chat community, and one week for a bulletin board community [18]. OUICs are similar to the latter one, thus, we collected data for 7 days from 15 April to 21 April 2016. One week data collecting was also applied in other online community research (e.g., [40]). The data we automatically collected include when and how many posts were written, the user's ID, and the tags of posts which show "repost" or "original". We then manually deleted the reposted post data because they were not originally created, and therefore, cannot be involved in activity evaluation in terms of innovation. Second, by utilizing the abovementioned activity evaluation model, we had activity score distributions during time interval Δt, as shown in Figure 3.

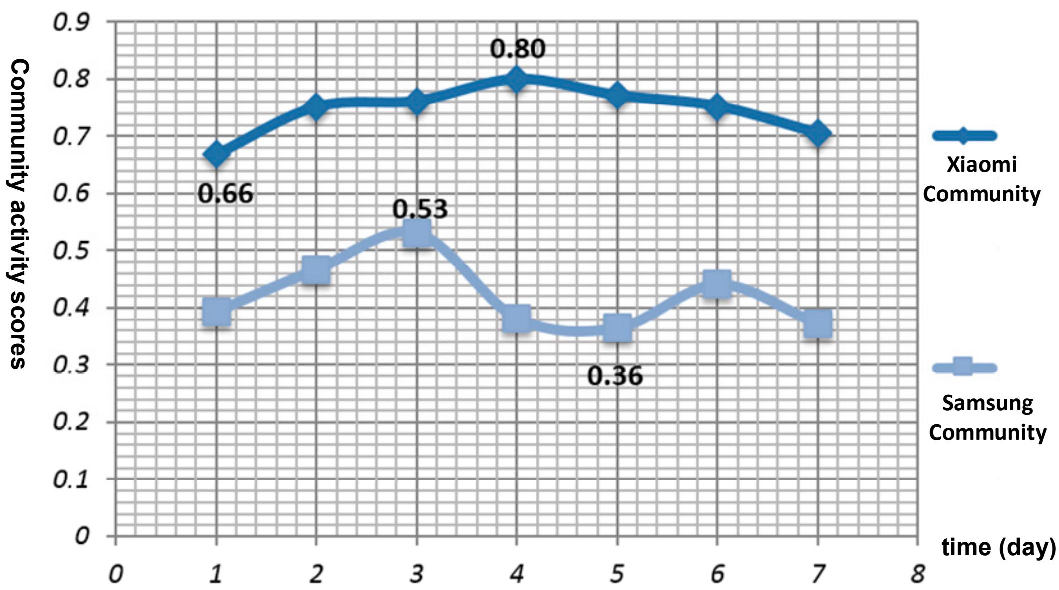

Figure 3. Activity Scores Distribution of Xiaomi Community and Samsung Community.

It can be found that the activity of Xiaomi community was moderate over the 7-day period. The activity scores of Xiaomi community were floating between 0.66 and 0.80. The activity of Samsung community was also moderate, but obviously lower than Xiaomi community. Its activity scores ranged from 0.36 to 0.53.

Figures 4 and 5 show the cumulative probability distribution of Xiaomi innovation community and Samsung community being an active community in the time period. The activity level of Xiaomi community is high, and Samsung community is moderate.

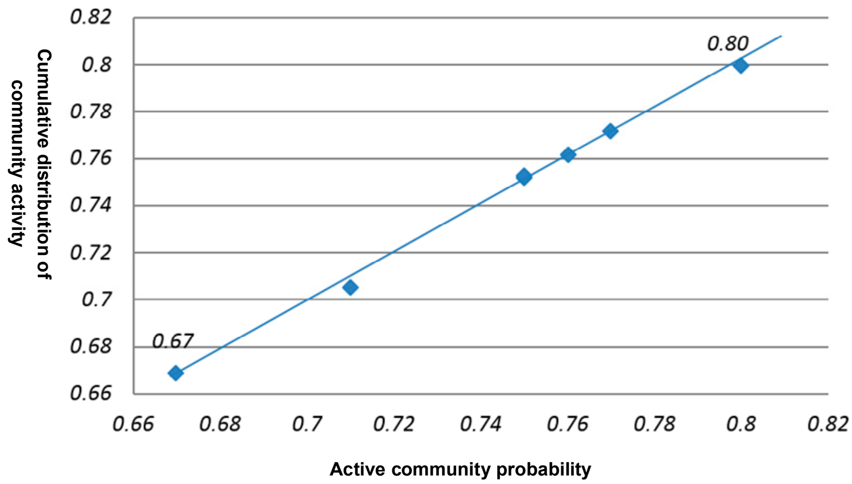

Figure 4. Active Community Probability Distribution of Xiaomi Community.

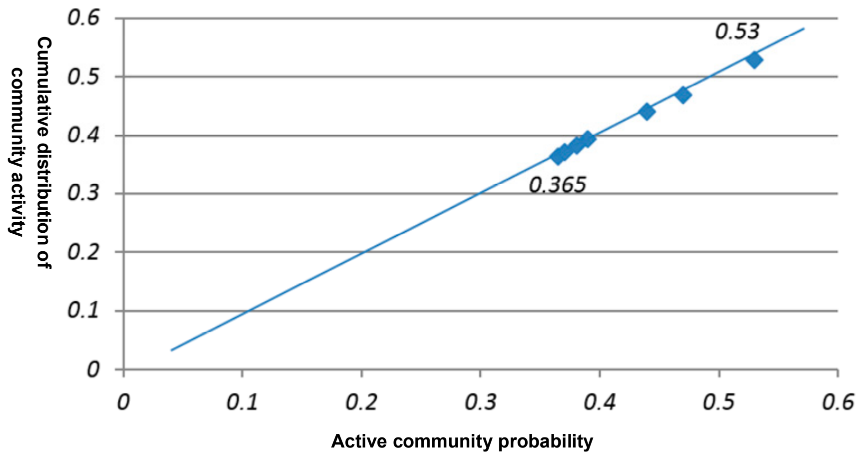

Figure 5. Active Community Probability Distribution of Samsung Community.

4. Impact Factors of Interaction in OUICs

4.1. The Relationship between Activity of User Innovation Community and Interaction

After evaluating the activity of OUICs, we also try to explore the impact factors of activity in OUICs so as to improve the quality of communities. To this end, we needed to understand what kind of user behavior influences activity. In this study, we mainly focus on interaction because user participation in OUICs correlated with interaction significantly [41]. The higher the frequency of user interaction, the higher the frequency of all activities in the community. The more users interact in the community, the more active the community will be. Interaction is also an information exchanging process of the community. Thus, companies can improve activity of OUIC through increasing users' interaction. We divided interaction into three categories according to the characteristics of OUICs [25,42]. Definitions of interaction are shown in Table 2.

Table 2. Definitions of Interaction.

Interaction	Definition
Content interaction	A kind of interactive activity where users are searching and browsing for a product, brand, and related information [25].
Human–computer interaction	A kind of interactive activity where users interact with the community's hypertext content, such as selecting community tools to search and browse information they need [43,44].
Interpersonal interaction	A kind of interactive activity where users communicate with other users or manage the online user innovation community [25].

Users' participation in activities of OUICs are the following types: (1) Searching for related information of products or services, such as price and function. This type of user activity can be classified as content interaction, which is the most basic community activity. (2) Using community tools to select, browse content, and other operations. This type of user activity can be classified as human–computer interaction. (3) Sharing experiences and product or services related information with other users and community managers. This type of user activity can be classified as interpersonal interaction, which is the most common user activity in the community.

4.2. Theoretical Framework

User's interaction in OUICs is an important behavior. If companies want to make users actively interact in their OUIC, they need to let users accept the community first. Based on the technology acceptance model [45], users' willingness of participating in communities is affected by the perceived usefulness and ease of use. Companies need to make sure services in the community are useful, and the services can meet users' needs before making them participate in community interaction. According to Maslow's hierarchy of needs theory [46], it is suggested that community can meet people's high-level needs, which are social needs, esteem needs, and personal actualization needs. It was our observation that the main purposes of OUIC interaction are as follows: accessing interesting information, using community tools, social communication, participating in recreational activities, and personal actualization. Therefore, the factors that affect interaction in OUICs can be reasonably classified into environmental factors, information factors, personal factors, and trust factors. The specifications of the factors are shown in Table 3.

Table 3. The Specifications of Four Impact Factors.

Factors	Specification
Environmental factors	Referring to the structure of OUIC, including community tools, incentives and response mechanisms, and so on [47].
Information factors	Meaning that in order to meet the needs of users in OUIC, the company provides them with product- or service-related information. Therefore, the users know more about the company and its products or services [47,48].
Personal factors	Personal factors mainly take motivation of users participating in interaction into consideration, including socializing, recreation, and personal realization. Users need to interact with others to socialize, thus promoting interpersonal interaction [48–50].
Trust factors	Trust factors mainly take into account familiarity and trust between users, or between the community and users. In order to make users talk freely in the community and provide effective and innovative ideas, the company needs to improve their understanding between each other [51].

As mentioned earlier, there are three kinds of interaction in OUICs. By promoting participation of users in these three types of interaction, companies can effectively improve activity of OUICs. Therefore, we propose our theoretical framework in Figure 6.

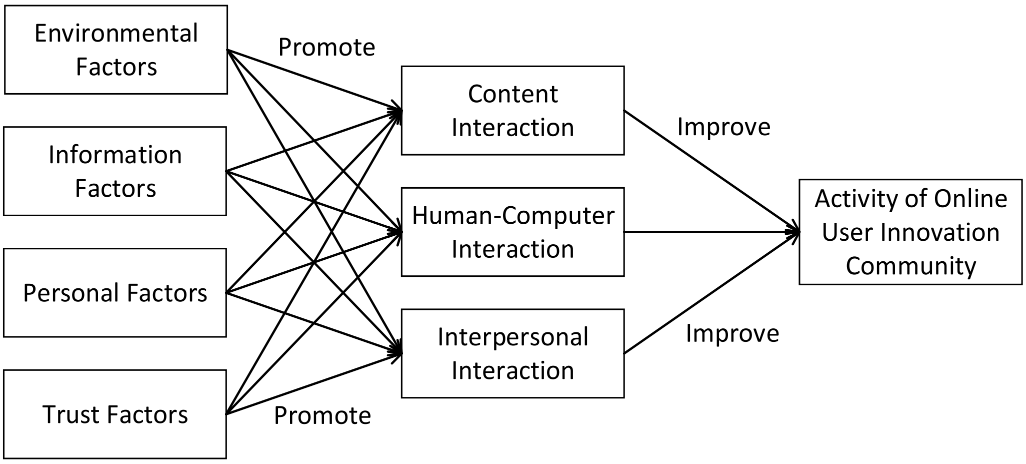

Figure 6. Theoretical Framework.

4.3. Hypotheses Development

Interaction plays a very important role in OUICs [32], which requires participation of all parties in a community. The reason why community users are willing to participate in interaction is because of their needs. Environmental factors, information factors, personal factors, and trust factors all have a great impact on interaction. Here, environmental factors refer to the factors in an online environment, rather than natural environment [52]. For example, they include online community tools, incentives for users participating in community activities, online automatic response mechanisms or online staff services, and others. Online environments usually provide technical support for users to participate in the community interaction. Sometimes, users need to solve product or service issues by applying community tools, which leads to content interaction. In this case, users would necessarily care about specific information of the products and services. In an OUIC, good incentives will provide users with some prizes or some special community gift points, and promote users to participate in community activities, resulting in better interpersonal interaction. A quick response mechanism allows users to receive a prompt response after sending a request to community, which promotes human–computer interaction. Therefore, we propose the following hypotheses regarding the relationship between environmental factors and community interaction:

Hypothesis 1 (H1). *Environmental factors promote interaction in online user innovation community.*

Hypothesis 1.1 (H1.1). *Environmental factors promote content interaction in online user innovation community.*

Hypothesis 1.2 (H1.2). *Environmental factors promote human–computer interaction in online user innovation community.*

Hypothesis 1.3 (H1.3). *Environmental factors promote interpersonal interaction in online user innovation community.*

Online communities have turned out to be the new form of socialization platform for fulfilling certain needs, such as providing or acquiring information [53]. Information value is an important factor in online communities [54]. Online communities can create positive effects in brand equity by providing an important source of information, particularly from their users [55]. With respect to OUICs, innovative information provided by users is also very valuable [12]. Users are likely to participate in all kinds of interaction during the process of acquiring and sharing information from OUICs. Users would interact with the online community website when looking for products or services, like clicking related posts and viewing them. This kind of behavior thus promotes human–computer interaction. In addition, many users become more like fans or supporters to the companies or community [56]. At Niketalk, for example, enthusiastic Nike fans even create their own basketball shoe designs and develop new shoe features [15]. In OUICs of smartphone industry, users like to discuss the performance and quality of a smartphone. In that process, users would share product information and product usage experiences with others, and then produce interpersonal interaction. Therefore, given the relationship between information factors and community interaction, we propose the following hypotheses:

Hypothesis 2 (**H2**)**.** *Information factors promote interaction in online user innovation community.*

Hypothesis 2.1 (**H2.1**)**.** *Information factors promote content interaction in online user innovation community.*

Hypothesis 2.2 (**H2.2**)**.** *Information factors promote human–computer interaction in online user innovation community.*

Hypothesis 2.3 (**H2.3**)**.** *Information factors promote interpersonal interaction in online user innovation community.*

There are some investigations regarding online communities that have suggested hierarchical needs theory [46] as an appropriate method of understanding and supporting users of online communities [57]. People will seek higher levels of demand after they meet their physiological needs and safety needs. In this study, we adopt and test the applicability of Maslow's hierarchy of needs in the OUIC context. Personal factors mainly take the motivation of users participating in interaction into consideration, including socializing, recreation, and self-actualization. In some innovative online communities (e.g., photography and music communities), the opportunity to present their skills motivates people to contribute, and the main motivation is to gain diverse feedback on creative work [58–60]. In the meantime, users gain recognition and compliments from others. The satisfaction of some individual needs by the online platform has been considered as an important determinant of user participation [61]. Therefore, in this way, the motivation of people participating in OUICs promotes interpersonal interaction. With respect to recreation, some OUICs provide users online games, to increase their activity. Recreation requires users to interact with the website, which causing human–computer interaction in OUICs. Realization of user's personal value is mainly reflected in their innovative ideas and suggestions for products or services. In doing so, users need to deeply understand the characteristics of the product or service, thus promoting the content interaction. Therefore, we propose the following hypotheses:

Hypothesis 3 (**H3**)**.** *Personal factors promote interaction in online user innovation community.*

Hypothesis 3.1 (**H3.1**)**.** *Personal factors promote content interaction in online user innovation community.*

Hypothesis 3.2 (**H3.2**)**.** *Personal factors promote human–computer interaction in online user innovation community.*

Hypothesis 3.3 (**H3.3**)**.** *Personal factors promote interpersonal interaction in online user innovation community.*

One of the most difficult challenges faced by online communities is cultivating knowledge sharing and trust [62,63]. Users rely on trust information to make decisions in online communities [51]. Trust builds and maintains exchange relationships, which can lead to quality knowledge sharing [64], and therefore, be beneficial to interaction in communities. The interaction among people is a complex relationship. Trust factors mainly take into account the familiarity and trust among users, or between the community and users. The nature of online interaction, without the cues that face-to-face contact affords, requires trust for successful communication [65]. Meanwhile, on the other hand, interaction also help to increase trust. The higher the trustworthiness of an OUIC, the more active the interaction will be, and thus, improve interpersonal interaction and human–computer interaction. With trust and familiarity in the community, users will trust the products and services more, and have a greater interest in them than in a low trust situation. In this case, content interaction of the community will also be increased. Therefore, we propose the following hypotheses:

Hypothesis 4 (H4). *Trust factors promote interaction in online user innovation community.*

Hypothesis 4.1 (H4.1). *Trust factors promote content interaction in online user innovation community.*

Hypothesis 4.2 (H4.2). *Trust factors promote human–computer interaction in online user innovation community.*

Hypothesis 4.3 (H4.3). *Trust factors promote interpersonal interaction in online user innovation community.*

4.4. Research Design and Data Collection

In the second study of this paper, we try to use an empirical method to examine the factors that affect interaction in OUICs. To this end, we looked through many OUICs of smartphone companies (e.g., HUAWEI, Xiaomi, Meizu, and OPPO) and understood their basic community framework. We then designed a questionnaire for users in the OUICs. A pilot survey was conducted by a group of students in university. Afterwards, we modified our questionnaire with some suggestions of professors in business school. A final questionnaire was created in an electronic form, and therefore, was easy to send through online platforms, like Sina Weibo, WeChat, and QQ. We sent the questionnaires in April 2016. The respondents were mainly college students or fresh college graduates. A total of 174 questionnaires were sent, and 125 of them were recollected. We verified the questionnaires by follow the steps: (1) check respondents' IP address, removing the questionnaires with the same IP address; (2) remove the questionnaires answering all questions with the same selection. After removing unqualified questionnaires, like uncompleted ones, we finally received 106 of them, which yielded a response rate of 60.9%. This is a relatively high response rate, and more than acceptable compared with some other surveys in online community-related research [66,67].

Among the 106 respondents, 50.94% were male and 49.06% were female, showing a good gender distribution of this survey. More than half of the respondents (64.15%) were 20 to 30 years old. Respondents who use HUAWEI community, Xiaomi community, Meizu community, and Apple's community accounted for 29.24%, 32.07%, 21.70%, and 7.55%, respectively. The rest of them used Samsung community, Vivo community, OPPO community, etc.

4.5. Data Analysis and Results

To examine the reliability and validity of our research, we conducted the following data analysis. The reliability analysis of each scale in the questionnaire is shown in Table 4. The reliabilities of content interaction, interpersonal interaction, personal factors, and trust factors are larger than 0.8. The reliabilities of human–computer interaction, environmental factors, and information factors are larger than 0.7. The reliability coefficient (Cronbach's alpha) for the various measures exceeded the recommended minimum of 0.70 set by Fornell and Larcker [68]. In the online community setting, many other studies also had reliability coefficients ranging from the minimum number 0.7, which showed acceptable reliability (e.g., [66,69]). Further, as shown in the Appendix A, all the composite reliabilities of variables are larger than 0.8, showing reliabilities are acceptable, according to Nunnally [70].

Table 4. Reliability Analysis.

Variable	Number of Samples	Items	Cronbach's Alpha
Content Interaction	106	3	0.854
Human–Computer Interaction	106	3	0.799
Interpersonal Interaction	106	3	0.895
Environmental Factors	106	3	0.735
Information Factors	106	3	0.791
Personal Factors	106	3	0.869
Trust Factors	106	3	0.883

The validity analysis was done as shown in Table 5. The Kaiser-Mayer-Olkin(KMO) values of the content interaction, interpersonal interaction, personal factors, and trust factors are larger than 0.7, and the significant probability of approximate chi-square statistics of the Bartlett spherical test is 0.000, which is smaller than 0.01, indicating the reliabilities of these variables are good. The KMO values of human–computer interaction, environmental factors, and information factors are all larger than 0.6, the significant probability of the approximate chi-square method of Bartlett's test is 0.000, which is also smaller than 0.01. Therefore, the validity of all the variables is acceptable.

Table 5. Validity Analysis.

Variable	KMO	Bartlett's Test of Sphericity		
		Approximate Chi-Square	DF	Sig.
Content Interaction	0.733	136.960	3	0.000
Human–Computer Interaction	0.695	100.071	3	0.000
Interpersonal Interaction	0.745	186.349	3	0.000
Environmental Factors	0.655	72.094	3	0.000
Information Factors	0.671	101.036	3	0.000
Personal Factors	0.722	158.879	3	0.000
Trust Factors	0.745	169.694	3	0.000

We used Pearson correlation analysis to verify the relationship between impact factors and community interactions. The correlation matrix is shown in Table 6.

Table 6. Correlation Matrix.

	1	2	3	4	5	6	7
1. Content Interaction	1.00						
2. Human–Computer Interaction	0.662 **	1.00					
3. Interpersonal Interaction	0.538 **	0.797 **	1.00				
4. Environmental Factors	0.719 **	0.673 **	0.670 **	1.00			
5. Information Factors	0.642 **	0.714 **	0.632 **	0.812 **	1.00		
6. Personal Factors	0.588 **	0.737 **	0.707 **	0.625 **	0.679 **	1.00	
7. Trust Factors	0.586 **	0.765 **	0.771 **	0.729 **	0.728 **	0.775 **	1.00

** Correlation is significant at the 0.01 level (two-tailed).

There are significant positive correlations between environmental factors, information factors, and all the interactions in communities are at the significant level of 0.01. The correlation coefficients are larger than 0.6, which means strongly correlated. The correlation coefficient between human factors and human–computer interaction is larger than 0.6, showing a strong correlation, and the correlation coefficient of interaction with content is larger than 0.4, meaning a relatively strong correlation. The correlation coefficients between trust factors and human–computer interaction, interpersonal interaction, are larger than 0.6, showing a strong correlation. To sum up, all the factors have a strong correlation with the community interaction.

Based on our proposed hypotheses, we try to use multiple linear regression analysis to examine the relationship between the factors and community interaction. In the past tens of years, researchers have used the multiple regression analysis as a powerful tool because it allows one to model, statistically, the relationship between dependent variables and a set of independent variables [71]. It is one of regression analysis' goals to figure out independent variables influencing a dependent variable. The results are shown in Table 7. The environmental factors and personal factors have a significant effect on content interaction, as their p values are smaller than 0.001 and 0.05, respectively. The p values of information factors, personal factors, and trust factors with human–computer interaction are smaller than 0.05, namely, these factors are significantly affecting human–computer interaction. The interpersonal interaction is significantly improved by the environmental factors, personal factors, and trust factors, because their p values are also smaller than 0.05. In addition, the variance inflation factors (VIF) are smaller than 10. The problem of multicollinearity of independent variables in this model is, therefore, not significant. All the F values are significant, suggesting that all the regression models are valid.

Table 7. Multiple Linear Regression Analysis.

Variables	Content Interaction	Human–Computer Interaction	Interpersonal Interaction	VIF
Environmental Factors	0.549(4.508) ***	0.081(0.775)	0.226(2.082) *	3.334
Information Factors	0.075(.597)	0.215(2.009) *	−0.045(−0.409)	3.498
Personal Factors	0.233(2.215) *	0.288(3.066) **	0.254(2.602) *	2.693
Trust Factors	−0.049(−0.398)	0.327(3.098) **	0.443(4.039) ***	3.399
R^2	0.551	0.670	0.643	
Adj. R^2	0.533	0.657	0.629	
F-value	30.952 ***	51.191 ***	45.531 ***	

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$; Numbers are standardized coefficients and t-values within parentheses.

As shown in Table 8, most of the hypotheses were supported. Users participate in activities of OUICs for different kinds of needs. In reality, environmental factors, such as optimizing the community tools, incentives, and response mechanisms, play a significant role in promoting the content interaction and interpersonal interaction in OUICs. This is because users sometimes need to receive technical support or other online services from the community or other users, which is consistent with the regression results of this study. However, our results did not support the hypothesis that environmental factors promote human–computer interaction in OUIC. Human–computer interaction typically needs a relatively high-level application of environmental tools in OUICs, which are probably not good enough for promoting human–computer interaction for now. It is one suggestion that companies could work on that, in the future. Information factors promote users to visit the community, and thus improve human–computer interaction, which is also consistent with the results. Interpersonal interaction and content interaction in OUICs, however, are not likely promoted by information factors, according to the results. One possible explanation could be users may be focused on gaining information through interacting with community itself more than with other users. The hypotheses regarding personal factors were all supported, suggesting users' needs or higher-level demands are very important to the interactions in OUICs. Users can meet their recreation needs and value realization by the three kinds of interaction. With respect to trust factors, they promote human–computer interaction and interpersonal interaction in OUICs, but not likely promote content interaction. This may be because users are more sensitive to interactions with community and other users, than interactions with the content in OUICs. Although four out of twelve hypotheses were not supported, these unsupported factors still have a strong correlation relationship with interaction.

Table 8. Hypotheses Test Results.

Hypotheses	Results
H1.1: Environmental factors promote content interaction in OUIC	Supported
H1.2: Environmental factors promote human–computer interaction in OUIC	Fail
H1.3: Environmental factors promote interpersonal interaction in OUIC	Supported
H2.1: Information factors promote content interaction in OUIC	Fail
H2.2: Information factors promote human–computer interaction in OUIC	Supported
H2.3: Information factors promote interpersonal interaction in OUIC	Fail
H3.1: Personal factors promote content interaction in OUIC	Supported
H3.2: Personal factors promote human–computer interaction in OUIC	Supported
H3.3: Personal factors promote interpersonal interaction in OUIC	Supported
H4.1: Trust factors promote content interaction in OUIC	Fail
H4.2: Trust factors promote human–computer interaction in OUIC	Supported
H4.3: Trust factors promote interpersonal interaction in OUIC	Supported

5. Sustainable Interactive Management Strategies in OUIC

Activity is a very important indicator for online communities. An OUIC would be of better value if its users are barely active. Therefore, how to improve and maintain activity of OUICs has become a very important task for companies. Our research has revealed that activity can be increased by improving community interaction. The following management strategies are all coming from the four interaction factors. For specific OUIC, the company should refer to specific interaction factors, and make interactive management strategies for the corresponding innovation community to improve community activity.

5.1. Optimizing Environment and Tools of OUIC

OUICs should establish a good interactive environment and provide interaction tools for their users. Only then are the users able to communicate with each other freely. It is our observation that in some OUICs, like HUAWEI, Xiaomi, and Meizu communities, they do not grant access for new users to post in specific sections. Those new users have to do some tasks before expressing their opinions and suggestions on the sections. Some OUICs also failed to provide users with the tools to forward external links, causing a lot of unnecessary restrictions.

Therefore, companies might want to design more reasonable community tools to create a good interactive environment. In addition, the response mechanism of the innovation community could be further refined so that it can respond quickly to users' requests, and receive suggestions and comments from users. It is suggested that improving response speed will lead to more contributions to online communities [17]. If users perceive the company as being non-responsive or failing to listen to their ideas, they may become alienated, and the company can potentially lose a valuable external source of ideas [12]. As for incentive method, most OUICs in the smartphone industry built a prize system, which can stimulate users to participate in interaction, and provide suggestions for product or service innovation. Other OUICs can also follow this method to further improve the frequency of community interaction.

5.2. Processing Information

The product and/or service information in OUIC is what the users need in the first place. OUIC managers need to let the users believe in the information and give their feedback on the product or service. Therefore, the community needs to strictly control the information for users to get real information about products or services. OUIC managers need to strengthen supervision. Users are very different, and they share a variety of information. Sometimes the information that users searched is not what they want, and some information is even fake [72,73]. Hence, the community manager could set up a mechanism to identify real and fake information to ensure high credibility of the community. The main goal of OUICs is to get advice from a large number of users, and therefore, promote product and/or service innovation. If companies want to get valuable information from a large number of messages generated by users, they need to filter and classify messages and identify useful ones. It also allows users to easily search for interested information and meet their needs.

5.3. Building Social Platform and Providing Leisure Activities

OUIC can also be a social platform. Increasing numbers of users nowadays go to online communities to meet a higher level of demand, and sometimes, for an entertainment-oriented purpose [74]. Appropriate leisure activities and socialization can better promote users to participate in community interaction. In this regard, HUAWEI, Xiaomi, and Meizu community are doing well. They encourage users to have both online and offline activities, which can improve the users' loyalty to the community. Therefore, companies need to build a convenient and comfortable online social platform for users interacting with each other as friends. At the same time, the community can regularly hold online entertainment activities and games related to products or services, which can attract users to participate in community interaction in the long term.

5.4. Improving Trust

People's trust is relatively vulnerable in online communities, due to anonymity [75]. In this context, companies need to take appropriate measures to improve the user's trust and sense of belonging to the community.

First, companies need to make leading users, to guide other users. For example, in Xiaomi community, leading users are chosen in every major section to guide other users. They often actively express their views to promote other users to better participate in community interaction. Therefore, other OUICs can also learn from this, to increase community activity.

Second, setting trendy topics for users to discuss might also be a good idea. In some OUICs, managers regularly present some discussion topics in order to attract users to express their opinions. Therefore, community managers need to carefully design each topic and make sure the users are interested in it. In general, meaningful, challenging, and interesting topics can lead to better discussion and communication.

Third, users can be divided into certain groups through social network analysis. People usually have a stronger sense of trust in people who belong to the same group. OUICs can promote user interaction by associating users of the same regions or same attributes into the same group, which can facilitate communication among users and increase their trust. In this way, users in the corresponding forum section can communicate freely and express their views on products or services.

6. Discussion

Upgrading products or services in various industries become faster and faster in the internet era. Companies have to keep innovating if they want to win the fierce competition in market. Meanwhile, online social networks are getting popular and more prevalent. In this background, OUIC has become an important source for companies to collect innovative information. Therefore, the importance of OUICs raised our interest to study them. Companies have to ensure a promising development of OUIC in order to better obtain innovative resources. Like other online social platforms, activity of OUIC has become an important indicator of whether the community is developing normally. In this work, we made an attempt to shed light on how to evaluate activity in OUIC, and explore the impact factors of interaction in OUIC. To this end, we proposed an activity evaluation model. Then, we used the model to evaluate activities of Xiaomi community and Samsung community. A research model was proposed, and an empirical study on the interaction in OUICs was conducted. We hypothesized that four kinds of factors have positive influence on community interaction. Data was collected through an online questionnaire survey.

6.1. Major Research Findings

There are several major findings of this work. First, we found that the activity in Xiaomi community is higher than in Samsung community in a certain period of time (a week) by applying our proposed activity evaluation model. Users in Xiaomi community seemed more active in posting, concerning community news, participating in community activities, and discussing community topics. Second, users' participation in OUICs generally belongs to three types of interaction, namely, content interaction, human–computer interaction, and interpersonal interaction. It is revealed that four factors affect the interaction in OUICs, including environmental factors, information factors, personal factors, and trust factors. Third, our data analysis result shows that most of the factors have positive influence on the three kinds of interaction, and therefore, increase activity in OUICs. Inadequate interaction is often an important reason for low activity.

6.2. Research Contributions and Practical Implications

This study provides multifold research contributions. The first contribution is that we proposed an evaluation model for assessing activity in OUICs. To the best of our knowledge, this is a very early effort in the literature. We extracted indicators from a perspective of the whole community level, rather than individual user level, which has a better understanding of community activity in a big picture. There are extensive opportunities to examine online communities on the basis of our proposed evaluation model, because it should also be applicable to other kinds of online communities. Second, this work also shed light on open innovation literature. This is a new perspective to study open innovation community, rather than only focus on integrating users in OUIC and idea implementation. Therefore, more interesting research could be examining user's activity in such innovation communities, so as to gain more accurate and in-depth insights about market needs and consumer preferences. Third, we explored the four factors that affect interaction in OUICs. We also proposed a research model that explained the relationship among community activity, interaction in community, and the impact factors. Future research can utilize the four factors to conduct further research regarding online community.

This study also provides some important practical implications. Companies can use the activity evaluation model to assess their activity level of OUIC. Thus, they know the operation status of their communities. According to the impact factors and interaction in OUICs, companies are able to understand key issues of their communities. The proposed four suggestions and strategies should help companies to better operate and manage OUIC, and therefore enhance the competitiveness of companies. By doing so, companies and users have a better interaction and communication, which will contribute to success of products and/or services. In the context of innovation community, the advantage may seem more valuable. Companies can receive innovative ideas more effectively from their users, and produce better-customized products.

6.3. Limitations and Future Directions

There are several limitations of this research, which can be improved in future work. First, we only examined OUICs in the smartphone industry. There are a large number of OUICs in other industries, which may have differences with them in terms of community framework, community characteristics, user profiles, etc. Future research may have new findings in other industries. Second, although the evaluation result is fine, the activity evaluation model is actually a simple one without sophisticated mathematical evaluation. We can try to do more work on the model in the future to improve it. Another interesting research direction could be collaborative brand attack (CBA) in OUICs. It is still in an early stage, regarding CBA research in social media marketing. Any internet user can potentially set off a CBA and a large majority of internet users can collaboratively attack a company through its social media platforms [76]. It is possible that, therefore, users of OUICs can negatively influence companies. We can still use our proposed evaluation model to access activity in the context of a CBA in OUIC, so as to better monitor the status of the community. In addition, what are the impact factors of activity in a CBA in OUICs? How to prevent or mitigate such kind of collaborative user behaviors? All the relevant questions could be answered in future work.

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Appendix A. Constructs, Items, and Standardized Loadings

Content Interaction CR [1] = 0.911	1. Finding information about the use of the product.	0.805
	2. Finding technical information about the product.	0.826
	3. Finding information about marketing conditions of the product.	0.809
Human–Computer Interaction CR = 0.882	1. I like to browse the contents of different web pages.	0.630
	2. I think the user innovation community webpage design is very good.	0.813
	3. I often use the communication and social tools of the user innovation community.	0.817
Interpersonal Interaction CR = 0.934	1. I like to post in the user innovation community and want to get the response of other members.	0.857
	2. I like to participate in the topic discussion of the user innovation community and put forward my own views and suggestions.	0.854
	3. I communicate, share information and exchange feelings with familiar users in the user innovation community.	0.868
Environmental Factors CR = 0.848	1. I would like to use user innovation community tools to solve some problems of the product.	0.610
	2. I would like to get some rewards by participating in user innovation community activities.	0.672
	3. I get respond quickly when I provide my advice to the user innovation community.	0.807
Information Factors CR = 0.877	1. I want to get some useful information in the user innovation community.	0.594
	2. I want to share information and knowledge about the product with other users.	0.817
	3. I want to share information and knowledge regarding other than the product with other users.	0.840
Personal Factors CR = 0.920	1. When I feel bored, I would like to participate in user innovation community recreational activities.	0.837
	2. I hope to meet members who have similar interest with me in the user innovation community.	0.904
	3. I hope that my views and ideas can be recognized by the company.	0.754
Trust Factors CR = 0.928	1. The high degree of familiarity with the user innovation community allows me to better use community tools.	0.837
	2. I communicate freely with familiar and trusted members.	0.885
	3. I would like to provide my own views and suggestions on the product to a reputable user innovation community.	0.817

[1] CR = composite reliability.

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