Research on Knowledge Sharing Efficiency Evaluation of Open Innovation Community: A Case of Xiaomi Community

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Abstract. Under the platform economy, more and more enterprises attract users to participate in innovation by means of Open Innovation Communities (OIC) and improve organizational performance through knowledge sharing. How to evaluate the efficiency of knowledge sharing scientifically is of great significance. In this paper, a total of 61 "circles" datum of the Xiaomi community were acquired as examples and divided into categories, and they were evaluated the knowledge sharing efficiency using the three-stage DEA model. The results showed that environmental factors and random interference had a strong impact on the efficiency of knowledge sharing in the community of enterprises. The comprehensive technical efficiency of 91.67% of the "circles" decreased significantly after adjustment, mainly due to low scale efficiency. The number of users featured posts, the number of fans, employee participation and the percentage of authenticated users had a positive impact on the efficiency of knowledge sharing in the community, and the number of user posts and community size had a negative impact on the efficiency of the community knowledge sharing. Finally, it discussed countermeasures and suggestions to improve the efficiency of knowledge sharing in the enterprise-hosted community from three aspects: community scale, community incentive system, and personalized service.

Keywords: Open innovation community (OIC) · Knowledge sharing efficiency · Three-stage DEA model · Xiaomi community

1 Introduction

With the rapid development of the Internet and Web 2.0 technology level, virtual communities with online social functions have become an innovative platform for communication and knowledge sharing among members of all parties [1]. Open Innovation Community (OIC) is a virtual community for users to implement innovation activities, and an Internet platform for resource circulation, user participation in innovation and knowledge sharing [2]. From the viewpoint of the founding body, OIC can be divided into two types: the company's self-built type and the knowledge discussion type created by a third party. Domestic and international companies are increasingly starting to

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establish OIC, such as My Starbucks Idea, Niketalk, Haier Open Partnership Ecosystem, Xiaomi Community, Club of HUAWEI, and so on. OIC is an important environment for all participants to carry out knowledge sharing, and the effect of user knowledge sharing largely represents its development and construction level [3]. However, as the scale of the community continues to expand, the "knowledge trend" in the community is mainly dominated by the government, and the breadth of knowledge sharing in the community is not enough. Moreover, the community faces problems such as low user activity and low enthusiasm for knowledge sharing due to a flood of users who have been "diving" for a long time after entering the community. Therefore, community managers need to understand users' needs and study what factors influence users' knowledge sharing to develop targeted promotion strategies, mobilize community users' enthusiasm to participate in knowledge sharing, and promote enterprises to broaden the path of innovative knowledge acquisition, and promote knowledge sharing for enterprises' innovative activities.

2 Literature Review

There are impacts on behavior, mechanism and efficiency evaluation of knowledge sharing in OICs that have generated considerable recent research interest.

2.1 Research on Influencing Factors of User's Behavior Knowledge Sharing in OIC

Nambisa et al. showed that the degree of user self-presentation, available social learning opportunities, corporate recognition, and recognition of users with creative sharing experience have a significant positive effect on users' sustained creative sharing behavior [4]. A study by Zhou found that factors such as innovation self-efficacy, outcome expectation, and social identity have significant positive effects on the knowledge sharing behavior of users of OICs [5]. Ying et al. explored the positive impact of the satisfaction of three psychological needs-autonomy, relatedness, and competence-on user's knowledge sharing behavior through the mediating role of psychological ownership [6]. Scholars have studied the effects of personal, environmental, and psychological factors on OIC knowledge sharing, but most studies have focused on the single-factor level and have not explored the interplay between multiple factors.

2.2 Research on Knowledge Sharing Mechanism of OIC

Rajabion et al. classified the knowledge sharing mechanisms in OICs into three categories: social mechanisms, incentive mechanisms, and medical mechanisms [7]. Wang et al. explored the mechanism of virtual community rewards on explicit and tacit knowledge sharing in virtual communities using intrinsic motivation as a potential mediator and showed that virtual community rewards have significant effects on both explicit and tacit knowledge sharing, highlighting the role of hedonic and self-efficacy in mediating the relationship between rewards and tacit knowledge sharing [8]. Li et al. proposed an incentive mechanism for the knowledge sharing behavior of leading users in OICs based on evolutionary games and pointed out that incentives are beneficial to promote knowledge sharing [9]. Regarding the research on the knowledge sharing mechanism of open innovation communities, scholars have mostly focused on the governance mechanism and incentive mechanism, and the exploration of the knowledge sharing mechanism of OIC is yet to be enriched.

2.3 Research on Efficiency Evaluation of Knowledge Sharing in OIC

Lee et al. used the DEA-Malmquist index method to analyze the changes in knowledge sharing efficiency in communities at the organizational, sectoral, and community levels [10]. Zhang used fuzzy hierarchical analysis for OIC knowledge sharing performance evaluation [11]. Yuan. et al. used the SBM model to measure knowledge sharing efficiency in an online health community and used the Tobit model to analyze whether environmental factors (e.g., user factors, community factors) interfered with the knowledge sharing efficiency of the community [12]. The research methods mostly adopt traditional DEA methods, fuzzy hierarchical analysis, and SBM models to measure the knowledge sharing efficiency, without eliminating the interference of environmental factors and random errors in the efficiency.

Xiaomi Community is an official platform developed by Xiaomi to facilitate user communication, consultation, help, complaints and proposals, and it is also a typical representative of an enterprise OIC s with mature operation and high user activity in China. Xiaomi developed the MIUI system with 1/3 of the ideas coming from fans and 80% of the modifications coming from the Xiaomi community. Hence, the paper introduces a scheme that firstly a total of 12 types of “circles” with high activity in the Xiaomi community are selected as the research objects, secondly adopts a three-stage DEA model to measure the knowledge sharing efficiency of the enterprise self-built OICs. Then, eliminating the influence of environmental factors and random errors on the knowledge sharing efficiency of the enterprise self-built OICs reflects the actual value of the knowledge exchange efficiency of the enterprise self-built OICs more realistically. Finally, it proposes suggestions to promote the knowledge sharing efficiency of the OIC, furthermore, to provide reference and reference for the enterprise to build an OIC.

3 Variables Selection and Data Sources

3.1 Input and Output Variables Selection

Ren believes that knowledge sharing is achieved through the interactive communication of community members, and the posting behavior of users is one of the manifestations [15]. Therefore, the input variables selected in this paper mainly considered three dimensions of personnel, knowledge source and time input in knowledge sharing input, and number of users, number of posts, and discussion time were selected.

The number of views measures the breadth of knowledge dissemination in knowledge sharing output. The number of comments is an inaccessible part of knowledge sharing activities in the community, and its number reflects the breadth of knowledge sharing among users. The number of replies refers to the communication among responders, reflecting the deepening of knowledge sharing levels in the OIC and the depth of knowledge sharing among users [16]. Therefore, the number of views, comments and replies from the time of posting to the statistical time were selected as the knowledge sharing output indicators. Based on the principles of systematization, availability and operability of data, this paper constructed the evaluation index of knowledge sharing efficiency of OIC. As shown in Table 1.

Table 1. Input and output evaluation indicators

Indicator type	Indicator name	Indicator meaning
Input indicators	Users $X1$	The human input in knowledge sharing
	Posts X_2	Knowledge source input in knowledge sharing
	Discussion Time X_3	The time investment in knowledge sharing
Output indicators	Views Y_1	The breadth of knowledge dissemination
	Comments Y_2	The breadth of knowledge sharing among users
	Replies Y_3	The depth of knowledge sharing among users

3.2 Environmental Variables Selection

According to the research of Simar et al., environmental variables need to select factors that affect DMU efficiency but DMU is uncontrollable [17]. Zhao et al. pointed out that users are the fundamental factors that determine the quality and quantity of knowledge sharing [18]. Xie et al. concluded that the community environment has a significant positive effect on knowledge sharing [19]. In this paper, considering the characteristics of OICs and data availability, the internal influencing factors of knowledge sharing efficiency of enterprise OICs were classified into two types of factors: one was user

Table 2. Description of environment variables

Indicator dimension	Indicator name	Indicator meaning
User factors	User Posts E_1	Total number of user posts
	User featured posts E_2	The number of user's featured posts
	Fans E_3	Number of user fans
Community factors	Community scale E_4	The ratio of community participants to posts
	Employee participation E_5	The proportion of official employee posts to posts
	The proportion of authenticated users E_6	The proportion of personal tags among community posting users

factors that included the number of user posts, the number of users featured posts and the number of fans, another was community factors that included community scale, employee participation and the percentage of authenticate users. As shown in Table 2.

3.3 Data Sources and Processing

According to the activities of the Xiaomi community, the first 61 "circles" were selected, and divided into 12 categories due to the discussion content, including: "Mobile Phone", "Tablet PC", "MIUI System", "MIUI Application", "APP Circle", "Computer", "Wearable Device", "Daily Life", "MI Fans Circle", "Game", "TV" and "Smart life". Then, writing Python codes, it obtained data items that included user information, post information, and discussion information of the "Featured" section in the 12 categories of "circles" in the Xiaomi Community from 2020 to 2021.

Because the Xiaomi community was revamped and updated in October 2019, the earliest data available in the community was October 2019. Hence this paper screened out more than 800,000 pieces of data crawled and retained the data from 2020–2021. In this paper, 12 types of "circles" in the Xiaomi community were analyzed, therefore $n = 12$. As the research needs, the window width was chosen as 2 ($d = 2$). Therefore, there was 1 window in this paper, and the number of decision units was $n \times d$, or 24 decision units. The content of the community comments and replies was screened and found that there was the behavior of "bump", therefore invalid content in the comments and replies was eliminated. The correlation analysis of input and output variables of knowledge sharing in the "Featured" section of Xiaomi community's 12 "circles" was shown in Table 3, which showed that all variables were significant at the 1% significance level. In addition, it passed the correlation test, which was satisfied the "homogeneity" hypothesis of the model [20].

Table 3. Correlation analysis of input-output variables

Variables	X_1	X_2	X_3	Y_1	Y_2	Y_3
X_1	1					
X_2	0.812***	1				
X_3	0.824***	0.847***	1			
Y_1	0.927***	0.703***	0.758***	1		
Y_2	0.971***	0.747***	0.685***	0.906***	1	
Y_3	0.956***	0.800***	0.883***	0.970***	0.896***	1

Note: *** indicates significance at a 1% level of significance

4 Empirical Analysis

4.1 Analysis of Efficiency of Knowledge Sharing in OIC Based on Initial Data

MaxDea 8 software was used to calculate the initial value of knowledge sharing efficiency of the enterprise OIC and obtain the comprehensive technical efficiency (TE), pure technical efficiency (PTE), and scale efficiency (SE) of knowledge sharing in the Xiaomi community from 2020 to 2021. As shown in Table 4, η represents the efficiency of the mean annual.

The overall knowledge sharing efficiency of the enterprise OIC was not high. When the influence of environmental variables and random errors were not eliminated, the comprehensive technical efficiency of the Xiaomi community was 0.873 and 0.741 respectively, which was not effective for DMU. Only "MIUI System" was always DMU effective, whereas the comprehensive efficiency and the output level of "APP Circle", "Game" and "Smart Life" were low. During 2020- 2021, the comprehensive technical efficiency, pure technical efficiency, and scale efficiency of knowledge sharing in the Xiaomi community all showed a downward trend. Only the efficiency of "Daily Life" was improved to DEA effective, indicating that the community's utilization of input factors was still insufficient, and the scale structure of the community still had space for optimization. Meanwhile, the pure technical efficiency of the Xiaomi community was lower than the scale efficiency. Only 50% of the "circles" in the community had pure technical efficiency higher than the average level, and 66.67% of the "circles" had scale efficiency higher than the average level. It can be concluded that the lack of pure technical efficiency mainly affected the comprehensive efficiency of the enterprise OIC. It shows that there are still problems in the internal management technology of the enterprise OIC, which restrict the comprehensive efficiency of community knowledge sharing and need to be improved and adjusted according to the specific situation.

Table 4. DEA Knowledge Sharing Efficiency of 12 Types of "Circles" in Xiaomi Community

Circles	The year 2020			The year 2021			η
	TE	PTE	SE	TE	PTE	SE	
Mobile Phone	1.000	1.000	1.000	0.736	0.736	1.000	0.868
Tablet PC	1.000	1.000	1.000	0.704	0.729	0.966	0.852
MIUI System	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MIUI Application	0.835	0.840	0.994	0.663	0.672	0.987	0.749
APP Circle	0.769	0.781	0.985	0.553	0.972	0.569	0.661
Computer	0.787	0.959	0.821	0.708	0.852	0.831	0.748
Wearable Device	1.000	1.000	1.000	0.773	0.895	0.864	0.887
Daily Life	0.933	0.933	0.999	1.000	1.000	1.000	0.966
MI Fans Circle	1.000	1.000	1.000	0.802	0.810	0.991	0.901
Game	0.799	0.871	0.917	0.559	0.872	0.641	0.679
TV	0.653	0.845	0.772	0.791	1.000	0.791	0.722
Smart Life	0.698	0.757	0.922	0.600	0.659	0.911	0.649
Xiaomi Community	0.873	0.916	0.951	0.741	0.850	0.879	0.807

Referring to Liu's definition of the critical point [20], the PTE and SE mean values (0.883 and 0.915) of the enterprise OIC knowledge sharing are set as the critical point, and the PTE and SE that constitute the efficiency of community knowledge sharing are divided. The overall knowledge sharing efficiency of the OIC can be divided into three types (as shown in Fig. 1). The first category is "high-high". Hence, "MI Fans Circle", "Daily Life", "MIUI System" and "Wearable Device" had higher knowledge sharing efficiency and less space for improvement and needed to improve PTE and SE slightly. The second category is "high-low", it has two types. One is a "PTE high, SE low" type of "circle" that included "Computer", and "TV", another is an "SE high, PTE low" type of "circle" that included "Mobile Phone", "Tablet PC", "MIUI System" and "Smart Life", and more "circles" in the community needed to improve PTE. The third category is "low-low" that PTE and SE are lower than the critical point, which "Game" and "APP Circle" were owned in it and needed to improve both PTE and SE.

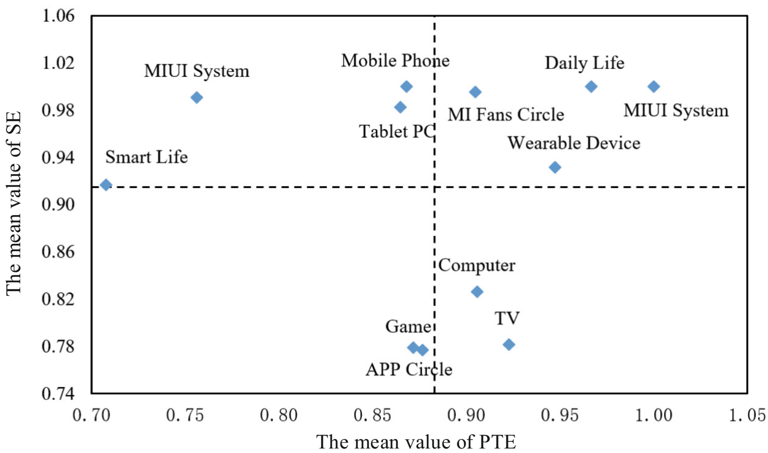

Fig. 1. Stage I: the classification by the mean value of PTE and SE in OIC

4.2 The Influences of Environmental Factors on Efficiency

Frontier 4.1 software was used to perform SFA regression on the input slack variables of decision making units and various environmental factors. As can be seen from Table 5, most of the regression coefficients of environmental variables (89%) had passed the significance test of 1% and 10%, and passed the mixed chi-square (LR) unilateral test at the significance level of 1%. It indicated that the SFA model was reasonable, and the selected six environmental variables were desirable, and each environmental variable had an impact on the input slack variables of the OIC. What is more, under the 1% significance level, the γ values of the three input slack variables tended to 1, which indicates that MI plays a dominant role in the knowledge sharing efficiency of OICs.

In the SFA regression model, if the coefficient value is positive, it shows that the increase of environmental variables will cause the increase of the slack variables, and if

Table 5. Regression results of the SFA model

Categories	Number of users slack variable	Number of posts slack variable	Lasting time slack variable
C	315.32^{***}	32.78^{***}	26893.71^{***}
E_1	11.96^{***}	–0.04	1116.59^{***}
$E2$	-33.30^{***}	0.84^{***}	-5976.32^{***}
$E3$	-0.01^{***}	0.00	-0.73^{***}
E_4	13.93^{***}	-0.17^{*}	763.55^{***}
E_5	-3589.88^{***}	-50.04^{***}	-320903.29^{***}
E_6	-3383.72^{***}	-54.68^{***}	-382816.40^{***}
σ^2	10137236^{***}	4373.35^{***}	136648640000^{***}
Γ	0.99999999^{***}	0.99999999^{***}	0.99999999^{***}
Log likelihood	– 212.86	–118.38	– 327.72
LR test	9.83^{***}	14.84^{***}	7.97^{***}

Note: *, * *, * * * indicate significance at 10%, 5%, 1% levels, respectively

the coefficient value is negative, it indicates that the increase of environmental variables will reduce the slack variables. The specific analysis is as follows:

User factors. The number of user posts had a significant positive impact on the number of user slack variables and the discussion time slack variable. The number of user featured posts had a significant negative impact on the number of user slack variable and discussion time slack variable, and had a significant positive impact on the number of posts slack variable. The number of fans had a significant negative impact on the number of user slack variables and the discussion time slack variable. The results show that the more user posts, the less community user and discussion time, and the more user featured posts, the more community user and discussion time, however it is not conducive to the increase of community posts. In other words, blindly pursuing a large number of user posts, although it greatly increases the input of knowledge sources, users obtaining useful information from a large number of posts is very difficult, and community knowledge sharing efficiency is not high. On the other hand, the user featured posts set up by the community are high-quality content. Therefore, Users can accurately obtain useful information, and the creators of featured posts are more capable of solving users' problems, which is conducive to enhancing knowledge exchange among users and promoting the improvement of comprehensive technical efficiency of knowledge sharing in the enterprise OIC.

Community factors. The community size had a significant positive impact on the number of user slack variable and discussion time slack variable, and had a significant negative impact on the number of posts slack variable. The employee participation and the percentage of authenticated users had a significant negative impact on the slack variable of the three input variables. This shows that blindly expanding the scale of the community will cause a waste of personnel input and time input. Although the number of posts in the community has increased, it is not conducive to the high-quality development of the community. The employee participation and the percentage of authenticated users were proportional to the efficiency of knowledge sharing in the OIC, and the absolute value of these two environmental factors was much higher than other variables, indicating that the more employees participated in the OIC and the more high-quality users have a significant effect on the improvement of community knowledge sharing efficiency. Hence, compared with blindly expanding the size of the community, efficient and reasonable management and attracting more high-quality users can promote the sharing of knowledge in the OIC, moreover enhancing the efficiency of knowledge sharing in the community.

4.3 Analysis of Efficiency of Knowledge Sharing in OIC Based on Adjusted Data

By eliminating the influence of environmental variables and random errors, adjusting the original data, and using MaxDea 8 software to recalculate, the knowledge sharing efficiency of the third-stage enterprise OIC is obtained. As shown in Table 6, η represents the efficiency of the mean annual.

Table 6. Stage III DEA: Knowledge Sharing Efficiency of 12 Types of "Circles" in Xiaomi Community

Circles	The year 2020			The year 2021			η
	TE	PTE	SE	TE	PTE	SE	
Mobile Phone	1.000	1.000	1.000	0.773	0.794	0.974	0.886
Tablet PC	0.087	0.856	0.102	0.566	0.846	0.670	0.327
MIUI System	1.000	1.000	1.000	1.000	1.000	1.000	1.000
MIUI Application	0.749	0.892	0.839	0.473	0.919	0.515	0.611
APP Circle	0.354	0.769	0.460	0.296	0.820	0.361	0.325
Computer	0.107	1.000	0.107	0.406	0.849	0.478	0.257
Wearable Device	0.977	1.000	0.977	0.650	1.000	0.650	0.813
Daily Life	0.525	0.696	0.754	0.086	1.000	0.086	0.305
MI Fans Circle	1.000	1.000	1.000	0.741	0.823	0.900	0.870
Game	0.518	1.000	0.518	0.250	1.000	0.250	0.384
TV	0.070	0.857	0.081	0.257	0.861	0.299	0.163
Smart Life	0.141	0.628	0.224	0.376	0.854	0.440	0.259
Xiaomi Community	0.544	0.892	0.589	0.489	0.897	0.552	0.517

Comparing Tables 4 and 6, it can be seen that the knowledge sharing efficiency of the adjusted enterprise OIC was significantly lower than that of the first-stage. In other words, after eliminating the influence of environmental factors and random interference, the average value of comprehensive technical efficiency and scale efficiency of knowledge sharing in the Xiaomi community was significantly lower than that before adjustment, and the average value of pure technical efficiency was slightly higher than that before adjustment (0.011), which indicates that the external environment has a strong influence on the comprehensive technical efficiency of knowledge sharing in Xiaomi community, and if the influence of environmental factors is not eliminated, the comprehensive technical efficiency of Xiaomi community will be overestimated. In addition, the low scale efficiency was the main reason for the low comprehensive technical efficiency in the third stage of the Xiaomi community. By moderately expanding the scale of community development, reducing resource waste and improving the level of organization and management, the knowledge sharing efficiency of the enterprise OIC consequently has 48.30% rising space.

Specifically, after input adjustment, only the “MIUI System” was in the production frontier, indicating that its knowledge sharing was indeed efficient after removing the impact of environmental and random factors. As the most discussed and concerned “circles” in the Xiaomi community, “MIUI System” was indeed at the leading level in technology and management. In terms of pure technical efficiency, including one pure technical effective “circle”, 66.67% of the “circles” had higher PTE after the adjustment than before the adjustment, indicating that the previous inefficiency was mainly affected by the environmental or random disturbance, and the external environment was an unfavorable factor for the internal management ability of the community. In terms of scale efficiency, 91.67% of the “circles” SE after adjustment was lower than that before adjustment, indicating that a favorable environment and active management strategy were conducive to scale increase, whereas the community itself should improve management level to adapt to environmental development.

Adjusted region division based on efficiency critical point. With reference to the previous classification, (0.894, 0.570) was the critical value after adjustment (see Fig. 2). Analyzing Tables 4, 6, and Fig. 2, it can be seen that the change range of SE in all “circles” was higher than that of PTE, indicating that environmental factors mainly affected the scale efficiency of knowledge sharing in the enterprise OIC.

With the first category of “high-high”, after adjustment, “Mobile Phone” and “MIUI Application” were changed from “high-low” to “high-high”, which indicated that environmental factors and random errors mainly affected its PTE, therefore improving technical efficiency and management level was likely to achieve DEA effectively. With the second category of “high-low”, “Game” changed from “low-low” to “high-low”, and the pure technology was effective, indicating that the internal resource allocation of the “circles” was reasonable, however the scale efficiency needed to be improved. With the third category of “low-low”, 41.67% of the “circles” pure technical efficiency and scale efficiency was lower than the community average, which had a lot of space for growth and needed to manage and scale.

4.4 Further Discussion

Based on the empirical research results of knowledge sharing efficiency of enterprise OICs, to improve the knowledge sharing efficiency of enterprise OICs and help enterprises make full use of knowledge resources:

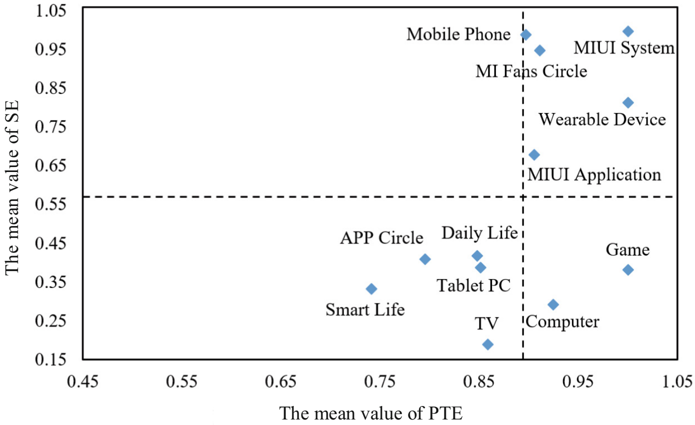

Fig. 2. Stage III: the classification by the mean value of PTE and SE in OIC

For lack of scale efficiency, low efficiency of knowledge sharing. Firstly, enterprise OICs should pay attention to community scale construction and improve the overall allocation of community resources. Secondly, it should establish a sound community management system, create a unique community culture, and enhance the user's sense of belonging and identity. Finally, it should pay attention to the high-quality presentation of knowledge sources, should screen high-quality posting content and strictly prohibit "bump" behavior, and promote effective knowledge sharing in enterprise OICs.

Based on the influence of environmental factors on the efficiency of knowledge sharing in the enterprise OIC, the results show that the quality of community members and the participation of employees have a promoting effect on the efficiency of knowledge sharing. It is necessary to explore high-quality original creators, and improve community incentive policies and internal incentive systems. What is more, the main concern of enterprises should not be to disseminate marketing information, but should focus on building community value.

The enterprise OIC should pay attention to the personalized recommendation algorithm, carry out accurate knowledge push, and meet the knowledge needs of different users. When the push content of the enterprise OIC is consistent with the user's knowledge sharing willingness, it is easier to arouse the resonance between the user and the community, and further, stimulate the user's knowledge sharing behavior.

5 Conclusion and Prospect

This paper used the three-stage DEA model to measure the knowledge sharing efficiency of the Xiaomi community during 2020–2021, and draws the following conclusions:

After eliminating the influence of environmental factors and random errors, 91.67% of the "circles" had a significant decrease in overall technical efficiency and scale efficiency and a slight increase in pure technical efficiency. For the enterprise OIC, the external environment has a strong influence on the efficiency of community knowledge sharing, resulting in a false high comprehensive technical efficiency before adjustment and a low scale efficiency, which is the main reason for the low comprehensive technical efficiency in the third-stage of the enterprise OIC.

The knowledge sharing efficiency of enterprise OICs is greatly influenced by environmental factors. The number of user posts was negatively correlated with personnel input and time input, and only increasing knowledge source input was not conducive to improving knowledge sharing efficiency. The number of user featured posts and fans was positively correlated with personnel input and time input, and high-quality knowledge exchange and user authority can promote the improvement of the enterprise OIC knowledge sharing efficiency. Community size was negatively correlated with personnel input and time input, which affected the improvement of knowledge sharing efficiency. However, employee participation and the percentage of authenticated users had positive effects on the knowledge sharing efficiency of the enterprise OIC.

Enterprise OICs can be divided into three categories. For “high-high” OICs, knowledge sharing within the community is ideal, and the maximum output can be achieved with the given input. For “high-low” OICs, the scale of the community should be adjusted and resource allocation should be rationalized, or community knowledge management and institutional changes should be emphasized to enhance the efficiency of knowledge sharing. For “low-low” OICs, they should start from both management level and scale expansion, increase personnel and resource investment, and improve overall technical efficiency.

Due to the revision of the Xiaomi community and the degree of data openness, the volume of data used in the study is relatively small and the environmental variables are not perfect. In the subsequent study, to expect to get more perfect knowledge sharing research results of enterprise OICs, it can add different communities for comparison, and improve the way of collecting data to obtain more data volume and other environmental variables that affect efficiency.

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