Postprint: A Study on Measuring Knowledge Exchange Efficiency in Technical Q&A Communities Based on SBM-Malmquist

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Abstract

[Purpose / Significance] Currently, research on knowledge exchange in technical Q&A communities remains insufficient. This study aims to adopt Data Envelopment Analysis to examine the efficiency of knowledge exchange in technical Q&A communities, thereby identifying disparities and evolutionary patterns among different sections, and providing reference for improving community management and enhancing knowledge exchange efficiency.

[Method / Process] Having constructed an evaluation index system for knowledge exchange efficiency, this study selects 15 popular sections of the "OSChina" community as research samples, and calculates their static and dynamic efficiency values of knowledge exchange using the SBM model and Malmquist index, followed by in-depth analysis.

[Result / Conclusion] The average knowledge exchange efficiency among the 15 popular sections of the "OSChina" community is relatively good, yet substantial disparities exist between sections. The overall knowledge exchange efficiency demonstrates an upward trend, mainly attributable to a 19.50% increase in the technical progress change index, suggesting that technological advancement constitutes the primary driver for the rising knowledge exchange efficiency in the "OSChina" community. However, a certain degree of managerial inefficiency and suboptimal resource utilization have been observed.

Full Text

Research on Knowledge Exchange Efficiency Measurement of Technical Question-Answering Community Based on SBM-Malmquist

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Abstract

[**Purpose/Significance**] Current research on knowledge exchange in technical Q&A communities remains incomplete. This study employs Data Envelopment Analysis (DEA) to investigate knowledge exchange efficiency in technical Q&A communities, aiming to identify differences and changing patterns across various sections and provide references for improving community management and enhancing knowledge exchange efficiency.

[**Method/Process**] Based on a constructed knowledge exchange efficiency evaluation index system, 15 popular sections of the "OSCHINA" community were selected as research samples. The static and dynamic efficiency values of knowledge exchange were calculated and analyzed in depth using the SBM model and Malmquist index.

[**Result/Conclusion**] The average knowledge exchange efficiency among the 15 popular sections of the OSCHINA community is good, but significant gaps exist between sections. Overall knowledge exchange efficiency shows an upward trend, primarily driven by a 19.50% increase in the technological progress change index, indicating that technological revitalization is the main reason for the improved knowledge exchange efficiency in the OSCHINA community. However, certain management issues and low resource utilization rates remain problematic.

Keywords: technical question-answering community; SBM model; Malmquist index; knowledge exchange efficiency; OSCHINA

Introduction

With the vigorous development of network technology and the diversification of information exchange and dissemination methods, virtual communities have gradually become important media for people to exchange and acquire knowledge via the Internet. This has enabled the dissemination of knowledge stored in human minds that cannot be directly retrieved by search engines. As a special type of virtual community, professional online forums allow users to express opinions, share information, and obtain knowledge through posting and replying, breaking through the limitations of time and space in interpersonal communication. When users raise questions, the community attracts and mobilizes other users from various fields to answer questions or propose solutions. Through continuous consensus-building around a topic, network groups similar to real-world communities—virtual communities—are formed. In recent years, with the widespread application of IT technology, the scale of technical Q&A communities has gradually expanded. This study focuses on knowledge exchange efficiency in technical Q&A communities, proposing targeted optimization and management measures based on actual data results to enhance user knowledge exchange effects and innovation, thereby supporting the sustainable development of technical Q&A communities.

OSCHINA is currently the largest open-source technology community in China. Since its establishment in 2008, it has been committed to providing IT developers with a Q&A platform for discovering, using, and exchanging IT technologies. This study selects the 15 most popular tag sections in the OSCHINA community as data sources for user knowledge exchange. First, based on reviewing and summarizing existing literature, a corresponding evaluation index system is constructed to calculate input-output values for measuring knowledge exchange efficiency in technical Q&A communities. Second, the SBM (Slack Based Measure) model and Malmquist index from Data Envelopment Analysis are employed to calculate static and dynamic efficiency values of knowledge exchange. Third, based on the measurement results, the main factors affecting knowledge exchange efficiency in technical Q&A communities are analyzed. Finally, based on the conclusions, rational suggestions are proposed to provide references for promoting knowledge exchange and improving knowledge innovation levels in technical Q&A platforms.

Literature Review

Current domestic and international research on Q&A communities primarily focuses on user information behavior, answer quality, and community comparisons. Studies on user information behavior concentrate on knowledge contribution. For instance, Liu Yunong et al. used Zhihu' s "vaccine" topic as a sample to study the social network structure characteristics and influencing factors of virtual knowledge communities, finding that user relationships are multi-level and block-distributed, with two centers—knowledge producers and demanders—where core users are more inclined to contribute knowledge than peripheral users. Z. Liu et al. found that knowledge contribution behavior is a prerequisite for users to obtain needed information in Q&A communities, with factors such as user participation, interest, and relevance significantly influencing answering willingness. J. H. Jin et al. discovered that user self-presentation, recognition from other members, and social learning opportunities all positively affect knowledge contribution behavior.

Research on answer quality focuses primarily on influencing factor characteristics. For example, Shen Hongzhou et al. used Zhihu as a case study to identify 10 basic features with potential impact on answer content quality, finding that more labels on answer content lead to clearer key content and structure, higher answer quality, and that users more easily identify with emotionally positive answers. Wang Wei et al. focused on Zhihu, mining answer and author features, and built feature models through logistic regression, support vector machines, and random forests to comprehensively predict answer quality. Comparative studies between communities mainly focus on functional construction from operational perspectives. Li Dan compared Quora and Zhihu, analyzing product performance, operational management, and user characteristics, finding that Quora has more precise functional positioning and simpler functional divisions, offering more advantages and successful experiences than Zhihu. Wan Li measured knowledge exchange efficiency across 8 disciplines in two academic forums, finding that one forum had lower knowledge exchange and scale efficiency but higher pure technical efficiency than the other.

Existing research shows that domestic and international scholars have focused on knowledge contribution in Q&A communities, with few studying answer quality influencing factors, and even fewer conducting community comparisons—most of which are outdated and don' t reflect recent developments. Knowledge contribution primarily encompasses question-asking and information browsing, with question volume and browsing volume representing community activity levels. Therefore, this study uses knowledge contribution, a relatively mature concept in Q&A community research, as the index system, selecting popular featured sections that reflect topic usage as decision-making units to measure knowledge exchange efficiency in technical Q&A communities using DEA, thereby enriching Q&A community research.

Knowledge Exchange Efficiency

Currently, domestic and international scholars have not yet studied knowledge exchange efficiency in Q&A communities. Based on Pang Jiangang et al.' s definition of virtual academic communities, Q&A communities can be considered a subclass of virtual academic communities. Current research on knowledge exchange efficiency in virtual communities focuses on efficiency measurement and influencing factors. Efficiency measurement studies primarily employ DEA. For example, Zong Qianjin et al. first proposed a knowledge exchange efficiency evaluation index system in 2014, using DEA to conduct static analysis of 8 disciplines on ScienceNet blogs. Jin Sheng further expanded the Malmquist index method based on DEA to study knowledge exchange efficiency across 12 sections of a forum. Yang Ruixian et al. studied 5 sections of an online health community using a three-stage DEA model after excluding exogenous factors. A few scholars have used other methods: Pang Jiangang et al. used Stochastic Frontier Analysis (SFA) and Kernel methods to study knowledge exchange efficiency and its dynamic evolution in 3 sections of an economics forum; Hu Dehua et al. used genetic projection pursuit algorithms to comprehensively evaluate knowledge exchange efficiency across 16 sections of 4 academic virtual communities. Influencing factor studies primarily combine efficiency measurement with comprehensive analysis. For example, Wu Jialing used Super-SBM and Tobit models to analyze knowledge exchange efficiency and influencing factors in a forum; Yuan Yongxu et al. studied knowledge exchange efficiency and influencing factors in a health forum using SBM and Tobit models.

In summary, research on knowledge exchange efficiency in virtual communities focuses on efficiency measurement, mostly with distinct disciplinary characteristics (e.g., science and engineering forums, economics forums, medical forums), with few studies on highly active technical Q&A communities in recent years. Moreover, when using DEA for knowledge exchange efficiency measurement, the CCR and BCC models are commonly employed, with limited application of the SBM model combined with the Malmquist index. Addressing this gap, this study uses a combined evaluation method based on the SBM model and Malmquist index to measure knowledge exchange in technical Q&A communities and proposes rational suggestions.

Methodology

This study selects the 15 most popular tag sections in the OSCHINA community as Decision Making Units (DMUs), including "Java," "Android," "PHP," etc. In January 2021, using the "Octopus Collector" tool, data for the 15 sections from 2018-2020 were collected according to the corresponding index system. Post, reply data, timestamps, votes, and authors were organized and statistically analyzed to reflect actual knowledge exchange conditions.

3.2.1 SBM Model

The DEA model was proposed by A. Charnes, W. W. Cooper, and E. Rhodes in 1978 as a non-parametric method for evaluating the effectiveness of multiple inputs and outputs relative to the production frontier. Traditional DEA models include the constant returns to scale CCR model and variable returns to scale BCC model, which have been widely applied since their inception. However, traditional DEA models are "radial" and "angular" dual-measurement approaches. "Radial" requires inputs and outputs to change proportionally, while "angular" typically considers only one input or output orientation, ignoring calculation result deviations caused by slack variables in DMUs. After years of research, scholars have continuously added more constraints to traditional models, developing super-efficiency DEA, SBM, and EBM models. This study uses the SBM (Slack Based Measure) model proposed by K. Tone in 2001, which introduces slack variables into the objective function. Compared with traditional models, it avoids radial and angular problems, fully considers input and output slacks, yields relative efficiency values between [0,1], enhances credibility and accuracy of efficiency evaluation, and emphasizes knowledge exchange efficiency maximization. Therefore, this study uses the SBM model to calculate knowledge exchange efficiency in technical Q&A communities, enabling further optimization of input and output slack variables—using minimized slack variables as the objective function to indicate that fewer knowledge input redundancies and output deficiencies lead to higher knowledge exchange efficiency values.

The SBM model is shown in formula (1):

公式（1)

Where * represents the relative efficiency value of DMU; S1 and S2 are the numbers of expected and non-expected output elements; x0 and y0 represent the input and output vectors of DMU; X and Y represent the input and output matrices of DMU. DMU is efficient if and only if $* = 1$; DMU is inefficient when $0 \leq * < 1$.

3.2.2 Malmquist Index

The Malmquist index was proposed by Swedish economist S. Malmquist in 1953. Subsequently, R. Färe et al. combined it with DEA to measure production and operational efficiency issues, leading to widespread applications in finance, healthcare, and industry. The Malmquist index determines efficiency changes and development trends by comparing the distance function ratios of decision units between period t and t+1, compensating for traditional DEA' s inability to measure dynamic efficiency. Therefore, this study uses the Malmquist index to examine the evolution trend of total factor productivity in technical Q&A community knowledge exchange, which can be fully integrated with DEA to measure dynamic efficiency and better analyze community changes.

The Malmquist index is shown in formula (2):

公式（2)

Where xt and xt+1 represent R&D input quantities in periods t and t+1; yt and yt+1 represent R&D output quantities in periods t and t+1; tfpch, effch, techch, pech, and sech represent total factor productivity, technical efficiency change, technological progress, pure technical efficiency change, and scale efficiency change indices, respectively. If tfpch > 1, total factor productivity has improved, showing an overall upward trend; if tfpch = 1, total factor productivity remains unchanged, showing stable overall trends; if tfpch < 1, total factor productivity has decreased, showing overall regression.

Index System Construction

Technical Q&A communities are specialized platforms for technical exchange where users can achieve knowledge sharing, exchange, and innovation through the Internet. In technical Q&A communities, knowledge providers externalize tacit knowledge through posting, while knowledge users obtain needed information through browsing and can further externalize knowledge by combining it with their own knowledge reserves. Knowledge feedbackers provide feedback to knowledge providers through voting and commenting behaviors. The entire process achieves knowledge sharing, exchange, and innovation.

Based on Wan Li' s research and combined with the characteristics of knowledge exchange in technical Q&A communities, this study constructs an index system for knowledge exchange efficiency in technical Q&A communities, as shown in Table 1 :

Table 1 Evaluation Index System for Knowledge Exchange Efficiency in Technical Q&A Communities

Index	Indicator	Description
X1	User Count	Reflects personnel input in knowledge exchange
X2	Post Count	Reflects effort input in knowledge exchange
X3	Discussion Duration	Reflects time input in knowledge exchange
Y1	Browse Count	Reflects knowledge dissemination breadth among users
Y2	Reply Count	Reflects knowledge exchange intensity among users
Y3	Vote Count	Reflects knowledge exchange quality among users

(1) Input Indicator X1—User Count. Users are the main subjects of knowledge exchange in technical Q&A communities, and knowledge provision and dissemination depend on this subject. The user count in this study refers to the actual number of participants in knowledge exchange—those who post and reply in each section, excluding registered users or voters only, as these two types are not considered knowledge exchange inputs.

(2) Input Indicator X2—Post Count. Users post in corresponding sections based on discussion topics, and post count fully demonstrates user effort input in knowledge exchange in a particular field.

(3) Input Indicator X3—Discussion Duration. This measures the time span from the initial post to the last reply collected, reflecting the duration of knowledge exchange and users' time input throughout the knowledge exchange process.

(4) Output Indicator Y1—Browse Count. This represents the number of views for each post in each section up to the statistical time, directly reflecting user attention to post topics. Higher browse counts indicate broader information dissemination.

(5) Output Indicator Y2—Reply Count. This represents the number of replies users make to posts of interest. One user replying to different posts is counted by post number; multiple replies to the same post are counted as one.

Continuous replies to posts represent the process of further internalization and absorption of topics and are core indicators for evaluating knowledge exchange efficiency in technical Q&A communities. Reply count directly reflects topic popularity—more replies indicate higher knowledge exchange levels and greater dissemination influence.

(6) Output Indicator Y3—Vote Count. This represents users' upvotes and downvotes on answer accuracy, limited to one vote per user per post. Vote counts are closely related to post quality, helping users quickly identify higher-quality posts.

Results and Discussion

Descriptive Statistical Analysis

This study organized and statistically analyzed data from 15 popular tag sections in the OSCHINA community according to the index system, with results shown in Table 2 :

Table 2 Input and Output Data for 15 OSCHINA Community Sections (2018-2020)

[Table content showing sections: Android, MySQL, Spring, JFinal, Python, Eclipse, Linux, jQuery, Apache Tomcat, Ubuntu, CentOS, Android SDK, Apache ECharts, with columns for X1 (User Count), X2 (Post Count), X3 (Discussion Duration), Y1 (Browse Count), Y2 (Reply Count), Y3 (Vote Count) for each year]

As shown in Table 2, significant differences exist between sections. Generally, more input indicators correspond to more output indicators. For example, the Java section has the highest values for all three input indicators and correspondingly the highest values for all three output indicators. User count and post count show a basically proportional relationship—the Java section has the highest user and post counts, while sections with fewer users like jQuery and Ubuntu have fewer posts. More posts also correspond to longer discussion durations—the Java section' s average post count reaches 23,846.33, while Ubuntu' s is only 389.33.

Static Efficiency Analysis of Knowledge Exchange Using SBM Model

Based on the SBM non-oriented model in MaxDEA PRO 6.3 software, this study calculated input and output data for 15 popular OSCHINA community sections, obtaining comprehensive technical efficiency, pure technical efficiency, and scale efficiency values. Comprehensive technical efficiency measures whether existing input resources achieve optimal output states, assessing the overall management level of knowledge exchange in technical Q&A communities. Pure technical efficiency refers to the optimal input-output effect when input scale is consistent, evaluating the objective conditions of technical Q&A communities in terms of technology and management. Scale efficiency is the ratio of comprehensive technical efficiency to pure technical efficiency, referring to efficiency changes caused by growth in input indicators when technical factors remain unchanged, reflecting resource allocation conditions in technical Q&A communities.

According to Table 3 , the average comprehensive technical efficiency index of 15 OSCHINA community sections ranges between [0.652, 1], with an average of 0.841, indicating a good level. Between 2018-2020, 6, 9, and 7 sections respectively achieved DEA efficiency (comprehensive efficiency index = 1) each year. The comprehensive technical efficiency trends vary across sections, which this study classifies into four types:

1. **Mature Type**: Including Java, JFinal, and Apache ECharts sections. These three sections achieved DEA efficiency every year, indicating optimal overall management levels, reasonable combinations and scales of input-output elements, current positioning on the production frontier, and ideal knowledge exchange efficiency.

2. **Growth Type**: Including PHP, Linux, and CentOS sections. These three sections had low comprehensive technical efficiency values in 2018 but gradually developed over time, progressively achieving DEA efficiency.

3. **Fluctuating Type**: Including Android, MySQL, Spring, Eclipse, jQuery, Apache Tomcat, and Android SDK sections. These seven sections show unstable comprehensive technical efficiency development trends with fluctuations. MySQL and Apache Tomcat sections reached their lowest values in 2019, showing concave trend lines opening upward, while the other five sections reached their highest values in 2019, showing convex trend lines opening downward. Spring, jQuery, and Android SDK sections achieved DEA efficiency in 2019.

4. **Declining Type**: Including Python and Ubuntu sections. Both achieved DEA efficiency in 2018, with Ubuntu also achieving efficiency in 2019, but both showed significant downward trends in 2020.

Additionally, from the three-year average comprehensive technical efficiency values, inefficient units account for 80.00%, meaning most sections haven' t reached ideal states, with large gaps between top and bottom sections. The Android and Eclipse sections never achieved efficiency over the three years, with Eclipse having the lowest efficiency value at only 0.652, indicating major problems in input, output, and management that warrant future attention.

As shown in Figure 1 [Figure 1: see original paper], the average efficiency value across sections was 0.829 in 2018, with 9 sections above the mean; in 2019, the average reached 0.927, significantly higher than 2018, with 11 sections above the mean; in 2020, the average dropped dramatically to 0.767, with 8 sections above the mean. The average knowledge exchange efficiency of the 15 sections shows certain fluctuations, most notably in 2020 when the Eclipse section reached an extremely low value of 0.423, indicating that major events like the pandemic caused significant differences in knowledge exchange efficiency across sections.

Figure 1 Comprehensive Technical Efficiency Changes in 15 OSCHINA Popular Sections

According to Table 4 , reasons for unit inefficiency can be divided into three categories:

1. **Pure Technical Efficiency Efficient but Scale Efficiency Inefficient**: In 2018, PHP, Spring, Linux, and Apache Tomcat sections; in 2019, Python section; and in 2020, MySQL, jQuery, and Ubuntu sections all achieved pure technical efficiency of 1 but had inefficient scale efficiency ranging between [0.427, 0.966], with large gaps between sections. This indicates relatively sound existing technology and management levels, with adequate utilization of technical inputs to ensure knowledge exchange efficiency under constant scale, but input redundancy caused by unreasonable scale structures leads to underutilized resources. Only by reasonably improving scale structure can comprehensive technical efficiency be effectively enhanced to achieve DEA efficiency.

2. **Scale Efficiency Efficient but Pure Technical Efficiency Inefficient**: Currently, only the Android section achieved scale efficiency of 1 in 2019 while pure technical efficiency was inefficient, indicating reasonable scale structure and high resource allocation capability, with adequate utilization of input elements and high output efficiency, but poor current technology and management levels constrain comprehensive technical efficiency improvement. This section needs to strengthen internal management, introduce advanced technology and equipment, and establish certain technical barriers to improve pure technical efficiency.

3. **Both Pure Technical Efficiency and Scale Efficiency Inefficient**: During 2018-2020, the proportion of such sections was 55.56%, 66.67%, and 62.50% respectively, indicating simultaneous problems in resource allocation and technical management that both require strengthening. In the third category, only the jQuery section in 2018 showed relatively high pure technical efficiency but low scale efficiency, while other sections showed relatively low pure technical efficiency but high scale efficiency, with scale efficiency ranging between [0.827, 0.986], where inefficient values are relatively concentrated with small gaps from efficient values. This indicates that scale efficiency is easier to improve through refined community management and reasonable input-output configuration to achieve comprehensive technical efficiency. However, pure technical efficiency has greater room for improvement, requiring strengthened institutional and technical management constraints, active measures to increase user and post counts, reduce unnecessary outputs, improve post quality, and promote effective utilization of input elements to continuously enhance pure technical efficiency. Notably, Android and Eclipse sections never achieved efficiency over the three years.

The analysis reveals that OSCHINA community sections with DEA inefficiency commonly suffer from low scale efficiency, indicating that scale expansion has been neglected during knowledge exchange and should receive more attention in future development regarding reasonable input-output configuration. Although multiple sections show pure technical efficiency, the polarization phenomenon remains severe compared to scale efficiency value ranges, constraining comprehensive technical efficiency improvement. Future efforts should continuously strengthen technical management levels and institutional constraints, establish reciprocal policies that stimulate user participation, and promote reasonable utilization of input resources to improve knowledge exchange quality.

Dynamic Efficiency Analysis of Knowledge Exchange Using Malmquist Index

The above SBM model analysis of OSCHINA community knowledge exchange efficiency represents static analysis at time points. To further explore internal factors and trends in knowledge exchange efficiency changes, this study uses MaxDEA8 software to calculate total factor productivity index (tfpch), technical efficiency change index (effch), and technological progress change index (techch) for the 15 popular sections between 2018-2020. The effch index measures DMU proximity to the production frontier, reflecting each section' s effective utilization capability of existing resources, determined by pure technical efficiency (pech) and scale efficiency (sech). The techch index represents changes in optimal efficiency values across periods, measuring whether technological innovation in each section changes with the production frontier. These indicators can intuitively reflect objective conditions of dynamic efficiency in knowledge exchange across sections.

Table 5 shows Malmquist index changes in the OSCHINA community from 2018-2020. From the total factor productivity perspective, the overall average is 1.156, with an average annual growth rate of 15.60%, and each period index exceeds 1, indicating an upward trend in knowledge exchange efficiency. From the technical efficiency perspective, the overall average is 0.967, showing a downward trend primarily due to a 25.90% decline in 2019-2020. From the technological progress perspective, the overall average is 1.195, increasing by 19.50%, indicating an upward trend in overall technological progress change index, mainly benefiting from a 41.40% increase in 2019-2020. This demonstrates that technological revitalization is the main reason for improved knowledge exchange efficiency in the OSCHINA community. However, both pure technical efficiency and scale efficiency show downward trends, with average declines of 1.30% and 2.00% respectively, which to some extent limit technical efficiency improvement—consistent with results from Table 3.

Table 5 OSCHINA Community Malmquist Index (2018-2020)

[Table showing tfpch, effch, techch, pech, sech indices for 2018-2019, 2019-2020, and 2018-2020]

Comprehensive analysis reveals that the OSCHINA community has good knowledge exchange efficiency, with total factor productivity showing an upward trend during 2018-2020. To explore deeper reasons, the following sections analyze Malmquist indices for all periods and sub-periods across the 15 popular sections.

Table 6 shows full-period Malmquist indices for the 15 OSCHINA sections. Approximately 66.67% of sections show total factor productivity growth, with an average increase of 15.60% across all sections. Technical efficiency change index shows an average decline of 3.30%, while technological progress change index shows an average increase of 19.50%, thereby driving up total factor productivity. Figure 2 [Figure 2: see original paper] clearly shows that the growth driver for OSCHINA community total factor productivity is technological progress, benefiting from China' s significantly improved IT technology level in recent years. The JFinal section stands out with total factor productivity growth up to 107.8%, primarily attributed to technological progress increasing by 107.8%. Among sections with declining total factor productivity (33.3%), Java and Apache ECharts mainly experienced technological progress decline, Python and Eclipse experienced technical efficiency regression, while Spring experienced declines in both technological progress and technical efficiency. Figure 3 [Figure 3: see original paper] reveals that although pure technical efficiency and scale efficiency absolutely influence technical efficiency, for most sections with declining technical efficiency, scale efficiency also declines while pure technical efficiency doesn' t show similar patterns, indicating that existing resource structure and scale integration should be strengthened to improve innovation levels and apply innovative inputs to key technologies and core information R&D, thereby improving resource allocation and driving technical efficiency improvement.

Table 6 Full-Period Malmquist Indices by OSCHINA Section

[Table showing effch, techch, tfpch for each section across 2018-2020]

Figure 2 Decomposition of Total Factor Productivity by OSCHINA Section

Figure 3 Radar Chart of Technical Efficiency Decomposition by OSCHINA Section

Table 7 shows dynamic Malmquist index changes by sub-period. During 2018-2019, 53.33% of sections showed total factor productivity growth, with more than half increasing over 50%, averaging 11.20% growth across 15 sections. Both technical efficiency and technological progress showed synchronous growth, indicating proper management and good technological development, with the Android section being most prominent at 2.887 total factor productivity. During 2019-2020, 53.33% of sections maintained total factor productivity growth, but technical efficiency declined while technological progress increased significantly. Technical efficiency regression resulted from 6.90% and 9.20% declines in pure technical efficiency and scale efficiency respectively, indicating that although technological development continued to rise, low resource utilization levels caused unbalanced development and certain management issues. Figures 4 [Figure 4: see original paper] and 5 [Figure 5: see original paper] show differences between the 2019-2020 and 2018-2019 periods, confirming that while overall development was prominent in the second period, technical efficiency development constrained OSCHINA community' s overall development level.

Table 7 Sub-Period Malmquist Indices by OSCHINA Section (2018-2020)

[Table showing effch, techch, tfpch for each section in 2018-2019 and 2019-2020]

Figure 4 Trends in Total Factor Productivity Decomposition Changes Between Two Periods

Figure 5 Trends in Technical Efficiency Decomposition Changes Between Two Periods

Conclusions and Recommendations

Based on existing research, this study evaluates knowledge exchange efficiency in technical Q&A communities using SBM-Malmquist. Results show that during 2018-2020, the average knowledge exchange efficiency of 15 popular OSCHINA sections was good, but large gaps existed between sections, with only 3 sections achieving DEA efficiency annually. Average knowledge exchange efficiency showed a "first rising then falling" fluctuation, most evident in 2020, indicating that major events like the pandemic may cause significant declines in community knowledge exchange. Among inefficient units, only the Android section achieved scale efficiency in 2019, indicating uneven resource allocation levels across sections, with input resources not optimally configured and input redundancy leading to underutilized resources. Total factor productivity shows an upward trend with an average increase of 15.60%, while technical efficiency change shows a downward trend and technological progress change index shows a 19.50% increase, rising 41.40% in 2019-2020, fully demonstrating that technological revitalization is the main driver of improved knowledge exchange efficiency in the OSCHINA community. However, management imperfections and low resource utilization remain urgent issues to address.

Based on these findings, this study proposes the following recommendations from an operational management perspective to improve knowledge exchange efficiency in technical Q&A communities:

First, integrate technical Q&A community resource management. Community managers should benchmark advanced international technical Q&A communities based on their positioning, adopting effective improvement measures according to actual conditions. Simultaneously, they should reasonably position user groups, setting appropriate thresholds for mature sections like Java, JFinal, and Apache ECharts that consistently achieve DEA efficiency to ensure user quality and quantity while creating unique cultural atmospheres. Additionally, orderly community operation depends not only on user posting, voting, and browsing—managers should actively guide by regularly initiating discussions on timely hot topics to attract user participation. They should also avoid information explosion caused by community development, which leads to content duplication, low relevance, and quality information accumulation that affects user experience.

Second, optimize technical Q&A community resource allocation. Intensive management can be adopted for sections with low resource allocation levels, transitioning from quantitative improvement to qualitative control. Posts should be selectively screened based on content—for example, administrators can select featured posts and invite highly active and honored users to reply, while providing incentives like virtual community coins for users with relatively high reply and post quality. Simultaneously, optimize voting mechanisms by enabling voting functions for both re-repliers and posters under the same reply, and provide material and spiritual rewards to users with high vote counts to continuously adjust internal incentive mechanisms. Additionally, communities can set up practical tutorials with strong case studies for new users on homepages or function bars to improve user information literacy and stickiness, thereby optimizing output per unit input in technical Q&A communities.

Third, promote technological innovation in technical Q&A communities. Similar question push functions can be implemented—for example, locking users'interested question search processes and trajectories based on their posting, browsing, and replying behaviors, building user portraits through deep mining and clustering to enable more precise similar question pushes and timely recommendations of relevant comments, while setting up internal supervision to block harmful information and maximize users' acquisition of useful information. Additionally, advances in artificial intelligence technology can promote human-computer dialogue models in technical Q&A communities, matching databases to automatically reply to similar questions and guiding users to related fields or displaying recommendation functions similar to knowledge graphs based on user keywords, stimulating further user thinking and enhancing knowledge exchange efficiency.

This study' s research objects and methods have certain innovation, but also limitations. In the index system construction, "post vote count" was added as a new indicator based on technical Q&A community characteristics, but the measurement only addressed knowledge exchange efficiency at the micro level. Macro-level influencing factors require further research. Therefore, in future follow-up studies, DEA can be combined with other methods to measure knowledge exchange efficiency while further analyzing influencing factors, thereby proposing deeper improvement recommendations for technical Q&A communities.

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Author Contributions

Ding Nan: Designed and improved the research framework, revised the paper.
Cao Weizhuo: Proposed the research topic, collected and analyzed data, wrote and revised the paper.
Xiang Mengmeng: Participated in designing the research framework and approach.

Note: Figure translations are in progress. See original paper for figures.