A Study on the Influencing Factors of Knowledge Recombination in Open Innovation Communities: A Case Study of Thingiverse (Postprint)

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Date: 2023-10-08T00:00:00+00:00

Abstract

[Purpose / Significance] This study investigates the influencing factors of knowledge recombination in open innovation communities, providing guidance and reference for user innovation and sustainable community development. [Method / Process] Based on the Elaboration Likelihood Model, we construct an influencing factor model for knowledge recombination in open innovation communities from two dimensions: knowledge characteristics and knowledge contributor characteristics. By crawling objective data from the 3D Printing module of the Thingiverse community, we conduct an empirical study on the influencing factors using negative binomial regression. [Results / Conclusions] In the central route, attention received and inheritability both exert significant positive effects on knowledge recombination, while complexity exerts a negative effect on knowledge recombination; in the peripheral route, knowledge contributor participation, in-degree centrality, and professional expertise level all exert significant positive effects on knowledge recombination.

Full Text

Research on Influencing Factors of Knowledge Remixing in Open Innovation Communities: Taking Thingiverse as an Example

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[**Purpose/Significance**] This study explores the influencing factors of knowledge remixing in open innovation communities to provide guidance and reference for user innovation and the sustainable development of such communities.

[**Method/Process**] Based on the Elaboration Likelihood Model (ELM), we construct an influencing factor model of knowledge remixing in open innovation communities from two dimensions: knowledge characteristics and knowledge contributor characteristics. By crawling objective data from the 3D Printing module of the Thingiverse community, we conduct an empirical study on the influencing factors using negative binomial regression. [**Result/Conclusion**] The results show that in the central path, attention and inheritance have significant positive effects on knowledge remixing, while complexity has a negative effect. In the peripheral path, knowledge contributor participation, inward social network centrality, and professional knowledge level all have significant positive impacts on knowledge remixing.

Keywords: open innovation community; elaboration likelihood model; knowledge remixing; influencing factors

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Introduction

With the development of Web 2.0 information technology, innovation no longer exists in isolation. An increasing number of well-known enterprises have established Open Innovation Communities (OICs) based on the internet to attract users to participate in innovation-related activities such as product ideation, research and development, and promotion. These communities have become an important source of enterprise product innovation [1]. Remix, as a crucial innovation model in OICs, generally refers to the "knowledge reuse" process that uses existing knowledge products in the community as raw materials or inspiration for further innovation, playing a vital role in internet-based innovation [2]. This new innovation model has greatly invigorated the community' s innovation atmosphere, and the large number of remixed products has doubled the community' s innovation output, making it the second largest source of innovation after original creation [3].

However, as communities develop, significant differences have emerged in the remix contributions of different knowledge products. Some knowledge products can be remixed multiple times by users, generating many unexpected remixes, while others remain ignored. Therefore, deeply exploring what types of knowledge products are easily remixed, helping communities quickly identify highly generative knowledge products, and leveraging the potential of existing innovations have become critical issues for the sustainable development of enterprise OICs.

Current academic research on remixing primarily focuses on online music communities, web communities, and OICs. Studies on influencing factors of remixing are mostly based on online music communities and web communities. On the one hand, examining content itself, G. Cheliotis et al. [4] studied influencing factors of music remixing in the online music community ccMixter, finding that popularity, derivativeness, and intertextuality significantly affect remixing.

B.M. Hill et al. [5] explored influencing factors of programming work remixing in the online programming community Scratch, discovering that complexity and cumulative count significantly impact remixing. On the other hand, creator characteristics also influence remixing—when selecting music works for remixing, users are affected not only by publication time but also by creator status and identifiability [6]. Research based on OICs has mainly concentrated on remix pattern analysis. M. Wirth et al. [7] identified ten unique remix patterns in the Thingiverse community using social network analysis, including linear evolution, merging, and forking. A few scholars have explored influencing factors of knowledge remixing in OICs, such as Y. Han et al. [8] examining the effects of popular topics and coded meta-knowledge on remixing during innovative knowledge reuse, and Tan Juan et al. [9] investigating the impacts of attention and knowledge complexity on knowledge product remixing in online innovation communities based on innovation diffusion theory.

In summary, existing research on remixing in OICs has primarily focused on remix pattern analysis and the impact of knowledge characteristics on remixing, with less consideration given to user individual characteristics as knowledge contributors, particularly how contributors' social networks influence remixing. Second, existing literature lacks a clear theoretical framework that combines knowledge characteristics and knowledge contributor characteristics to jointly explore influencing factors of knowledge remixing in OICs. Therefore, this study adopts the Elaboration Likelihood Model, uses the 3D Printing module of the Thingiverse community as the research object, and empirically analyzes influencing factors of knowledge remixing in OICs from both knowledge characteristics and knowledge contributor characteristics perspectives, further expanding research on remixing in OICs and providing a theoretical reference for future studies in this domain.

Theoretical Basis and Research Hypotheses

Elaboration Likelihood Model and Its Application

The Elaboration Likelihood Model (ELM), proposed by renowned social psychologists R. E. Petty and J. T. Cacioppo, is a theoretical framework used to explain attitude changes that may occur during the processing of persuasive information [10]. The model suggests that attitude and behavior changes in information receivers during information processing are primarily influenced by central and peripheral paths. In the central path, information receivers need to invest considerable cognitive effort to carefully analyze and think about argument cues related to information quality, thereby making corresponding cognitive judgments. In the peripheral path, information receivers typically do not need to expend much effort and only need to evaluate information based on heuristic cues related to the information content, making corresponding inferential judgments [11]. The ELM has been widely applied in research on online behaviors such as information adoption, knowledge dissemination, and knowledge payment. For example, C. Huo et al. [12] explored influencing factors of health information adoption on social media based on ELM, finding that information quality and information source credibility positively affect information adoption through the mediating variable of trust. Wang Zhiying et al. [13] constructed a safety emergency knowledge dissemination model based on ELM, discovering that knowledge quality and knowledge source characteristics significantly affect safety emergency knowledge dissemination during safety incidents. Wei Wu et al. [14] studied influencing factors of online knowledge payment users' continued payment intention based on ELM, finding that content quality and source credibility of knowledge products positively affect users' continued payment intention.

The essence of remixing is a process where OIC users continuously process existing knowledge products, similar to a persuasion process and analogous to information adoption. During the knowledge remixing process in OICs, users not only analyze the quality of knowledge itself but also pay attention to the credibility of knowledge contributors. Therefore, this study uses ELM to explain the knowledge remixing process in OICs, treating knowledge-related characteristics as the central path and knowledge contributor-related characteristics as the peripheral path to deeply explore the influencing mechanisms of knowledge remixing in OICs.

Central Path Hypotheses

The central path in ELM primarily involves judgment of knowledge quality, which is generally related to the characteristics of knowledge itself. This study uses the Thingiverse community as the research context and measures knowledge quality primarily based on knowledge attention, complexity, and inheritance.

2.2.1 Influence of Attention on Knowledge Remixing Attention refers to the degree to which a knowledge product receives attention from other community users. Related research indicates that innovative products with higher attention are more likely to become dominant products [9]. The primary motivation for OIC users to participate in knowledge remixing is learning, and selecting knowledge products with relative advantages during the remixing process leads to better learning outcomes [2]. By learning and understanding knowledge products with relative advantages, OIC users increase their knowledge reserves, thereby enhancing their innovation capabilities in the future and stimulating the generation of remixed products. Personal use is also considered an important motivation for knowledge remixing [15]—using existing innovative knowledge to create new knowledge that meets personal needs and benefits. This pragmatic motivation stimulates users to exert maximum effort to explore and continuously improve existing advantageous knowledge products. Therefore, compared with low-attention knowledge products, highly-attention knowledge products have higher relative advantages, are more likely to attract the attention of other community users, promote community users to evaluate and improve the knowledge product, and thus increase the likelihood of knowledge remixing. Hence, this study proposes the following hypothesis:

H1: In OICs, attention has a positive effect on remixing.

2.2.2 Influence of Complexity on Knowledge Remixing Complexity refers to the difficulty for community users to understand and use existing knowledge. In OICs, users have limited cognitive abilities and often struggle to understand highly complex knowledge products. When selecting knowledge products for remixing, OIC users fully consider the feasibility and practicality of the innovation process. Simple knowledge is easier for community users to understand and master, reducing many constraints for subsequent improvement and providing more open possibilities for future remixing innovation development. For example, in Linux open-source software, projects released in early stages were relatively simple with incomplete details, making them easier for potential contributors to understand and build, and providing more pathways for user participation in subsequent improvement [5]. Although highly complex knowledge may have high potential value, it can cause confusion in community users' cognition and understanding, and may have many limitations in subsequent use, resulting in low feasibility and difficulty in attracting other users' attention and participation. Therefore, this study proposes the following hypothesis:

H2: In OICs, complexity has a negative effect on remixing.

2.2.3 Influence of Inheritance on Knowledge Remixing Inheritance refers to the degree to which existing knowledge products inherit or transmit attributes or functions from previous-generation knowledge products [16]. Inheritance innovation involves multiple rounds of processing and iteration of knowledge products, unconstrained by limiting conditions, allowing them to continue remixing innovation along the original inheritance chain. In the online music community ccMixter, songs obtained through inheritance often gather the efforts and expertise of many users, making them more attractive for further remixing [17]. In OICs, innovatively inherited knowledge products have better compatibility compared to source innovations [18]. From the perspective of innovation diffusion theory, innovations compatible with previous ideas better conform to OIC users' existing cognitive patterns and thinking paradigms, making them more likely to be welcomed by community users, gain user acceptance and recognition, and thus facilitate further improvement of existing innovative knowledge. Therefore, this study proposes the following hypothesis:

H3: In OICs, inheritance has a positive effect on remixing.

Peripheral Path Hypotheses

The peripheral path in ELM primarily involves judgment of source credibility, which mainly derives from the reliability, authority, and professionalism of the information source [19]. Correspondingly, in the knowledge remixing process, knowledge contributors serve as the source of knowledge, and their characteristics significantly affect remixing. In the Thingiverse community, reliability derives from the trust gained through knowledge capital brought by knowledge contributor participation; authority is judged based on the social capital brought by knowledge contributors' social networks [20]; and professionalism derives from knowledge contributors' professional knowledge levels.

2.3.1 Influence of Participation on Knowledge Remixing Participation refers to the number of knowledge products published by knowledge contributors in OICs. The number of knowledge products published by users represents their enthusiasm for participating in innovation communities. Knowledge contributors who publish more knowledge products may possess more knowledge capital and be more trustworthy. Related research indicates that in online innovation communities, the more products a user publishes, the greater the breadth and depth of product knowledge cognitive diffusion [21]. Knowledge contributors who publish more knowledge products receive more feedback, and interaction and ideological exchange with other community users are more conducive to promoting knowledge contributors to accumulate more knowledge capital [22]. The more knowledge capital knowledge contributors accumulate, the more conducive it is for them to understand existing products and the market more clearly, further enhancing their innovation capabilities. As knowledge contributors' understanding of products and the market increases, the knowledge products they publish are more likely to have operational and economic value and are more likely to be remixed by community users. Therefore, this study proposes the following hypothesis:

H4: In OICs, participation has a positive effect on remixing.

2.3.2 Influence of Social Network on Knowledge Remixing Social network refers to the strength of social relationships between two different users within a community [23]. Existing research indicates that social networks can be measured by network centrality, divided into inward network centrality and outward network centrality [24]. Inward network centrality can directly reflect a user' s central position in the social network; users with high inward network centrality often occupy core positions in social networks and have high prestige and community influence [25]. For example, empirical research based on online video website data shows that social networks play an important role in the diffusion and influence process of user-created videos—the more subscribers a video creator has and the higher their inward network centrality, the faster their created videos spread and diffuse [26]. In the Thingiverse community, innovative users can also choose to follow other users they are interested in, and the number of followers can measure outward network centrality. Users with high outward network centrality can obtain more useful innovation information from the users they follow, with broader channels for acquiring innovation information. In summary, users with high inward network centrality have greater influence in the community, and their published innovations are more likely to receive attention and participation from their followers. Users with high outward network centrality can learn from the knowledge sharing of the users they follow, enhance their knowledge and skill reserves, compensate for their deficiencies, and thereby improve creativity, stimulating users to publish more high-quality innovative knowledge and attract other users' attention. Therefore, this study proposes the following hypotheses:

H5a: Inward network centrality has a positive effect on knowledge remixing.
H5b: Outward network centrality has a positive effect on knowledge remixing.

2.3.3 Influence of Professional Knowledge Level on Knowledge Remixing Professional knowledge level refers to the degree of mastery of relevant professional knowledge, experience, and skills by knowledge contributors. In OICs, users actively contribute ideas and participate in interactions based on their knowledge levels. Fan Zhe et al. found that mastery of professional knowledge positively affects users' community contribution behavior, and users with higher professional knowledge levels contribute more to the community and have higher authority [27]. In the Thingiverse community, users are required to fill in their 3D design skill levels, including novice, intermediate, and advanced. Users' professional knowledge levels can well explain the reliability of innovative knowledge sources, making the authority of knowledge recognized. Related research indicates that individual professional knowledge levels of users in OICs determine the quality of innovations they publish in the community [28]. The higher a user' s professional knowledge level, the richer their knowledge, experience, and skills, the higher the quality and persuasiveness of the products they provide, the more they can attract community users' attention, gain community users' trust, enhance users' perceived value, and ultimately affect the likelihood of remixing. Therefore, this study proposes the following hypothesis:

H6: In OICs, professional knowledge level has a positive effect on remixing.

Based on the above theoretical analysis and research hypotheses, this study constructs an ELM model of influencing factors of knowledge remixing in open innovation communities, as shown in Figure 1 [Figure 1: see original paper].

Research Design

Data Collection

Thingiverse is currently the world' s leading OIC for 3D printing model design. Since its establishment in November 2008, users have published over 1.6 million 3D printing designs under open license agreements, allowing other community members to comment on, print, make, and remix designs. The OIC has set up a "Remixed From" tag to record which products a design inherits from, and a "Remixes" tag to record how the design has been absorbed, improved, and re-innovated by other users. Therefore, the Thingiverse community is an ideal place to test the hypotheses of this study. This study selects the 3D Printing module in the Thingiverse community as the data source and uses Octoparse scraping software to collect design product information and design product contributor information from the module' s establishment to August 20, 2021. To ensure data validity, data with zero remix counts and null or abnormal values were removed, resulting in 6,051 valid data entries.

Variable Measurement

To verify the proposed research hypotheses, the measurement and explanation of dependent variables, independent variables, and control variables are shown in Table 1 .

3.2.1 Dependent Variable The dependent variable in this study is the number of remixes, represented by the number of Remixes displayed on the design homepage in the Thingiverse community.

3.2.2 Independent Variables **(1) Knowledge Characteristics.** Knowledge characteristics include attention, complexity, and inheritance. Attention is represented by the number of likes and comments a design receives. Thingiverse users express their preferences for design products through liking and commenting behaviors—the more likes and comments, the higher the attention the design receives. Complexity is represented by the number of downloadable files in the design page. Files are necessary conditions for printing designs; complex knowledge products usually require more files to print and take longer than simple knowledge products. Inheritance is represented by a dummy variable indicating whether the design itself was generated by inheriting from previous designs (0 = no, 1 = yes).

(2) Knowledge Contributor Characteristics. Knowledge contributor characteristics include participation, inward social network centrality, outward social network centrality, and professional knowledge level. Participation is represented by the number of designs displayed on the user homepage. Inward social network centrality is represented by the number of followers a knowledge contributor has, and outward social network centrality is represented by the number of other users the knowledge contributor follows. Professional knowledge level is represented by the 3D design skill level displayed on the user homepage. In the Thingiverse community, users are required to fill in their 3D design skill levels, including novice, intermediate, and advanced. This study encodes these three situations as three dummy variables: DSL1 represents novice, DSL2 represents intermediate, and DSL3 represents advanced.

3.2.3 Control Variables The longer a design is published, the more likely it is to be browsed by users and remixed. Therefore, to avoid differences in remix counts due to design publication time, this study selects design publication duration as a control variable, represented by the number of months between data collection and design publication time.

Regression Model Selection

Since the dependent variable (remix count) in this study is a count variable and the independent variables include numerical and categorical variables, a count model is appropriate for processing the sample. Count models include Poisson and negative binomial models. Since the Poisson model requires the mean and standard deviation of the dependent variable to be equal, while in this study' s sample data the mean is less than the standard deviation and overdispersion exists, the negative binomial regression model is more suitable for hypothesis testing.

Data Analysis

Descriptive Statistics

This study uses Stata 15.1 to conduct descriptive statistics on dependent variables, independent variables, and control variables. The specific results are shown in Table 2 .

As shown in Table 2, except for the inheritance, professional knowledge level, and publication duration variables, other independent variables have large data dispersion. To control for the influence of potential outliers and make regression results more robust, this study logarithmically transforms attention (likes and comments), complexity (files), participation (designs), inward social network (followers), and outward social network (following), defining them as lnLike, lnCom, lnFile, lnDes, lnFol1, and lnFol2 respectively. If zero values exist in variables during processing that cannot be directly log-transformed, ln(x+1) transformation is applied.

This study uses Stata 15.1 for regression analysis and hypothesis testing. The specific regression results are shown in Table 3 . Based on the Log likelihood Ratio significance and Pseudo R^2 values, the model fit of this study is good.

Variable Category	**Variable Name**	**Coef.**	**Std. Err.**
Knowledge Characteristics	lnLike	0.553***	
lnCom	0.241***		
lnFile	-0.134***		
RemixFrom	0.173***		
Contributor Characteristics	lnDes	0.037*	
lnFol1	0.034***		
lnFol2	-0.016		
DSL1	-0.072*		
DSL3	0.396***		
Control Variable	Duration	0.007***	

Variable Category	Variable Name	Coef.	Std. Err.
Constant	_{cons}	-2.928***	
Model Fit	Pseudo R^2	0.134	
Log likelihood	-2.3e+04		

Note: * significant at the 0.05 level (two-tailed), ** significant at the 0.01 level (two-tailed), *** significant at the 0.001 level (two-tailed).

(1) Influence of Central Path on Knowledge Remixing. The regression coefficient for like-based attention is 0.553 ($P < 0.001$), and for comment-based attention is 0.241 ($P < 0.001$), indicating that both like-based and comment-based attention have significant positive effects on remixing, supporting H1, with like-based attention having a greater impact than comment-based attention. The regression coefficient for complexity is -0.134 ($P < 0.001$), indicating that complexity has a significant negative effect on remixing. This shows that higher complexity makes it more difficult for users to understand and cognitively process, reducing the likelihood of remixing, supporting H2. The regression coefficient for inheritance is 0.173 ($P < 0.001$), indicating that inheritance has a positive effect on remixing. In the inheritance innovation process, inheritance behavior' s optimization and improvement of innovative knowledge represent important enhancements to source innovation, attracting more user attention and further innovation, supporting H3.

(2) Influence of Peripheral Path on Knowledge Remixing. The regression coefficient for knowledge contributor participation is 0.037 ($P < 0.05$), indicating that participation has a significant positive effect on remixing, supporting H4. The regression coefficient for inward social network centrality is 0.034 ($P < 0.001$), indicating that inward social network centrality significantly and positively affects remixing, supporting H5a. However, the regression coefficient for outward network centrality is -0.016 ($P > 0.05$), indicating that outward network centrality does not affect remixing. The reason may be that if a knowledge contributor has many followers, they are often community leaders with high professional knowledge and skills, and the knowledge products they publish have higher potential value, making them more likely to attract community attention and further innovation. In contrast, knowledge contributors who follow many others are often community followers with lower professional knowledge and skills, and the value of the knowledge products they publish is lower, making them less likely to gain user attention and trust. Therefore, H5b is not supported. Using intermediate professional knowledge level contributors as the reference group, the regression coefficient for novice professional knowledge level contributors is -0.072 ($P < 0.05$), indicating that novice professional knowledge level contributors have a lower impact on remixing than intermediate-level contributors. The regression coefficient for advanced professional knowledge level contributors is 0.396 ($P < 0.001$), indicating that advanced professional knowledge level contributors have a higher impact on remixing than intermediate-level contributors. This shows that the higher the professional knowledge level of knowledge contributors, the richer their knowledge, experience, and skills, and the higher the potential value of the knowledge products they publish, making them more likely to attract community users' attention, gain community users' trust, and further innovate, supporting H6.

Based on the negative binomial regression model analysis results, the verification results of the hypotheses proposed in this study are summarized in Table 4 .

Table 4 Summary of Hypothesis Verification Results

Hypothesis	Content	Verification Result
H1	Attention has a positive effect on remixing	Supported
H2	Complexity has a negative effect on remixing	Supported
H3	Inheritance has a positive effect on remixing	Supported
H4	Participation has a positive effect on remixing	Supported
H5a	Inward network centrality has a positive effect on remixing	Supported
H5b	Outward network centrality has a positive effect on remixing	Not Supported
H6	Professional knowledge level has a positive effect on remixing	Supported

Conclusions and Outlook

Research Conclusions

Based on the Elaboration Likelihood Model, this study constructs an influencing factor model of knowledge remixing in open innovation communities from two aspects: knowledge characteristics and knowledge contributor characteristics. By collecting real data from the 3D Printing module of the Thingiverse community and conducting empirical analysis on the theoretical model, the results show that in the central path, attention and inheritance have significant positive effects on knowledge remixing, while complexity has a negative effect. In the peripheral path, knowledge contributor participation, inward social network centrality, and professional knowledge level all have significant positive effects on knowledge remixing. This study makes important theoretical and practical contributions to research on remixing innovation and related fields in OICs.

In terms of theory, this study adopts the Elaboration Likelihood Model as the analytical framework and constructs an influencing factor model of knowledge remixing in OICs from a new perspective. Unlike previous studies, it explores influencing factors of knowledge remixing in OICs from two dimensions—knowledge characteristics and knowledge contributor characteristics—enriching research content on remixing in OICs and providing theoretical references for future research in the remixing domain.

In terms of practice, this study provides relevant countermeasures and suggestions for OIC user innovation and community management: (1) **Guidance for OIC user innovation.** Users should publish more precise, concise knowledge products that match their cognitive levels and have high comprehensibility to increase their likelihood of being remixed. Users should actively learn relevant professional knowledge and strive to improve their professional knowledge levels and cognitive abilities to gain recognition from other community users. (2) **Suggestions for OIC community managers to guide user remixing.** Community managers should attach importance to advantageous knowledge products with high attention, rank them according to like and comment counts, and use this ranking system to guide users to observe, learn, and improve innovations around highly-attention advantageous products, thereby creating more valuable remixed products. Community managers should focus on refined management of knowledge complexity, simplify users' cognitive understanding processes of knowledge products, and enhance the comprehensibility and feasibility of innovative knowledge by designing more refined sharing mechanisms. Community managers should emphasize the management of inherited knowledge products in the community and actively guide community users to pay attention to the "Remixed From" tag. Community managers should focus on guiding users' following behaviors to help community users expand their personal social networks in the community. Community managers should value user groups who actively participate in innovation and have advanced professional knowledge levels, design diversified incentive mechanisms to encourage them to continuously innovate, and create a positive innovation atmosphere.

This study still has some limitations: This study only selected one module (3D Printing) in the Thingiverse community for empirical research, with limited data collection scope, and the research results may not fully reflect the real situation. Future research can collect more comprehensive data and select similar communities for validation studies to improve the generalizability of conclusions.

The influencing factors of knowledge remixing explored in this study are not comprehensive enough; future research could consider more factors, such as comment quality or emotional factors affecting remixing. This study does not consider the relationships among various factors; the interaction effects among influencing factors and their mechanisms of influence on knowledge remixing are also worthy research directions.

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Author Contributions:
GAO Tian: Responsible for determining research ideas, data collation and analysis, and paper writing.
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Note: Figure translations are in progress. See original paper for figures.