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ABSTRACT

Potentially innovative ideas are being generated, shared, and even remixed (recombined) in the online innovation communities. These ideas create new innovations through remixing of ideas. In this study, we investigate how remixing makes ideas more innovative in online innovation communities. Our model is validated through ordinary least squares regression on a secondary dataset of 57,049 ideas collected from one of the largest 3D printing online innovation communities, Thingiverse.com. The result shows that the number of prior ideas has an inverted U-shaped relationship with the idea's degree of innovation and the cross-boundary remix has a positive effect on the idea's degree of innovation.

Keywords: remixing, innovation idea, prior ideas, cross-boundary remix, online innovation communities.

INTRODUCTION

With the recent development of the platform industry, the online innovation communities are also developing. Online innovation communities (OICs) are venues that give individuals the chance to exchange information, spark creativity, and promote the growth of innovation. (di Gangi & Wasko, 2009). In the past, when data was uploaded to a website for free, such as GitHub, other users could download or develop and upload it (Hata *et al*, 2022). According to Ye *et al*. (2012), OICs are crucial for the development of innovative ideas. OICs are characterized by Gebauer *et al*. (2013) as wealthy sources of innovation that provide its participants additional advantages.

The OICs are designed to enable users to come up with creative ideas. Additionally, OICs are now acknowledged as crucial contexts for academics to comprehend the processes of innovation, in addition to being significant sources of innovation (Flath *et al*. 2017). Innovation is the generation, acceptance, and implementation of new ideas (Thompson, 1965). Innovations wouldn't exist in a vacuum; rather, they need some recombining of already existing components (Schumpeter, 1942; Weitzman, 1998). It has been recently that the notion of innovation through recombinations has received significant interest, due to the rise of open platforms and online communities (Cheliotis *et al*., 2014; Oehlberg *et al*., 2015; Stanko, 2016). In addition, user community innovation has become widespread in the real world. (Anderson, 2012). Therefore, the individual's ideas (i.e. innovations) emerge more regularly and effortlessly. Such individual's ideas are highly innovative and often develop new products (Von Hippel, 2005).

The concept of reusing pre-existing elements to produce something new is frequently described by the term 'remixing,' an established in the music industry (Flath *et al*., 2017). However, remixing has frequently appeared not only in the music industry, but also within online platforms such as the OICs recently (Hill & Monroy-Hernandez 2013). The 2013 Green Paper on Copyright Policy, Creativity, and Innovation in the Digital Economy published by the U.S. Department of Commerce defines remixes as "works created through modifying and mixing existing works to make something new and creative." Accordingly, the literature related to remixing in the innovation communities is increasing. Studies on remixing in OICs have mainly been researched on remixing behavior (Stanko *et al*., 2021) and what factors are influencing which innovations to be remixed (Tan *et al*., 2020; Stanko, 2016). However, research on how remixing in OICs affects innovation ideas is sparse. This study identifies the impact of remixing on OICs in the current situation where various OICs are emerging. Therefore, our main research question is the following: How remixing makes ideas more innovative in OICs?

To answer this question, we collected data set from Thingiverse, one of the largest 3D printing OICs, and the findings of our study have several contributions. First, our study demonstrates an inverted U-shaped relationship between the number of prior ideas that were remixed and the degree of innovation of the new idea. The result indicates that, as the number of ideas used for remixing increases, the degree of innovation increases, but if too many ideas are used, the degree of innovation decreases. In addition, we examine the relationship between cross-boundary remix and an idea's degree of innovation. The result shows that the idea was more innovative when ideas were transferred to other fields during the remixing process.

LITERATURE REVIEW

The role of recombination in innovation

The terms *reuse*, *recombination*, and *remixing* are frequently used exchangeably. The management field has explored the problem of recombining existing ideas to produce something new. (Weitzman, 1998). Due to the development of online venues of information exchange, researchers' interest in the phenomena of recombinations has recently expanded. Schumpeter (1934) established the notion that innovation involves novel recombinations of information already in existence, which is where the idea of innovation as recombination first emerged. Such recombination-based innovation research has been conducted in the context of firm knowledge, scholarly knowledge production, patent, and open source development projects.

Scholarly knowledge production is one of the contexts in which the recombination for innovation has been studied. Uzzi *et al*. (2013) proposed that the most influential articles are likely to reference innovative combinations of prior information while still advancing conventional combinations. Similar to scholarly articles, patents contain references to other patents, and analyzing these references can help one grasp the context of a patented invention. (Albert *et al*., 1991; Almeida, 1996). The hypothesis that invention is a recombination process is supported by an analysis of patent citations (Katila & Ahuja, 2002). Furthermore, the analyses of a firm's recombination support the hypothesis that the recombination of internal as well as external knowledge of a company creates innovation (Kneeland *et al*., 2020; Arts & Fleming. 2018; Garriga *et al*., 2013). Even though recombination is frequently discussed, especially in relation to OICs, little is known about how much remixing contributes to innovation.

HYPOTHESES DEVELOPMENT

In the OICs, users share their ideas and other users remix ideas as the source of innovation. Users generate a large number of ideas on a daily basis in the OICs. When a user creates an idea using prior ideas on an OICs, the user creates an entirely new idea using at least one of those prior ideas. It is through these prior ideas that the basis of remix will be laid, as well as a variety of inspiration for remixers. Additionally, individuals with a deep knowledge of a particular domain possess a more complex knowledge structure, so they can consider a greater number of knowledge reconfigurations with the domain to produce novel outcomes (Taylor & Greve, 2006). The level of innovation in a remixed idea will therefore be higher if it is based on more prior ideas.

Although prior ideas should increase its degree of innovation, this would be useful only up to a certain extent. For remixers in OICs, a large number of prior ideas to remix something new would lead to the situation of information overload. When the amount of information being exceeded the individual's capacity to process it, the information overload occurs (Morwitz, 2012). Due to the variety of prior ideas, it may be difficult to manage the remixing process and would likely exhaust the remixer's creativity and productivity. Hence, we suggest that there is an inverted U-shaped relationship between the number of prior ideas and the degree of innovation of ideas with appropriate prior ideas being more likely to be innovative.

H1. There is an inverted U-shaped relationship between the number of prior ideas and the degree of innovation.

Ideas from various domains exist within OICs. With accessibility that is an advantage of OICs, remixers can seek and use the domains they want or encounter with relative simplicity. Moreover, by merely viewing dispersed knowledge, individuals will get inspiration from a variety of domains and develop their own novel and creative ideas. Through this process, existing ideas will be remixed and either used for a new purpose in a different area or exist for a similar purpose in the same area. According to a study by Fleming *et al*. (2001), combinations of familiar knowledge can lead to combination exhaustion, yet recombinations of distant knowledge can provide the source of novelty. Compared to combining elements from the same domain, combining elements from different domains, triggers novel outcomes (Savino *et al*., 2017). Therefore, even in the remix process, there will be a high degree of innovation if the prior idea's domain is shifted to a different domain. We propose that the cross-boundary remix is positively correlated with the idea's degree of innovation.

H2. The cross-boundary remix is positively correlated with the idea's degree of innovation.

DATA

Data source

To examine the relationship between the degree of innovation and remixing process, we obtained our dataset from Thingiverse (http://www.thingiverse.com) which is one of the largest online 3D printing innovation communities. Figure 1 shows the Thingiverse website's homepage. On Thingiverse, users can publish their ideas for the community to print, comment on, and even remix. Designers (idea publishers) upload the images of their 3D printable ideas together with one or more files required to print or remix the ideas. The Creative Common licenses available to Thingiverse creators often allow for more or fewer limitations on the use and remixing of their ideas. Each idea contains a diverse variety of information, such as the creator, posted date, images, category, user comments, description, likes, and downloads. It also includes self-reporting information about the number of times other users have printed an idea (number of makes) and the number of times that the idea has been remixed from others (number of remixes). It also contains optional information about any sources which the idea was 'remixed' from.

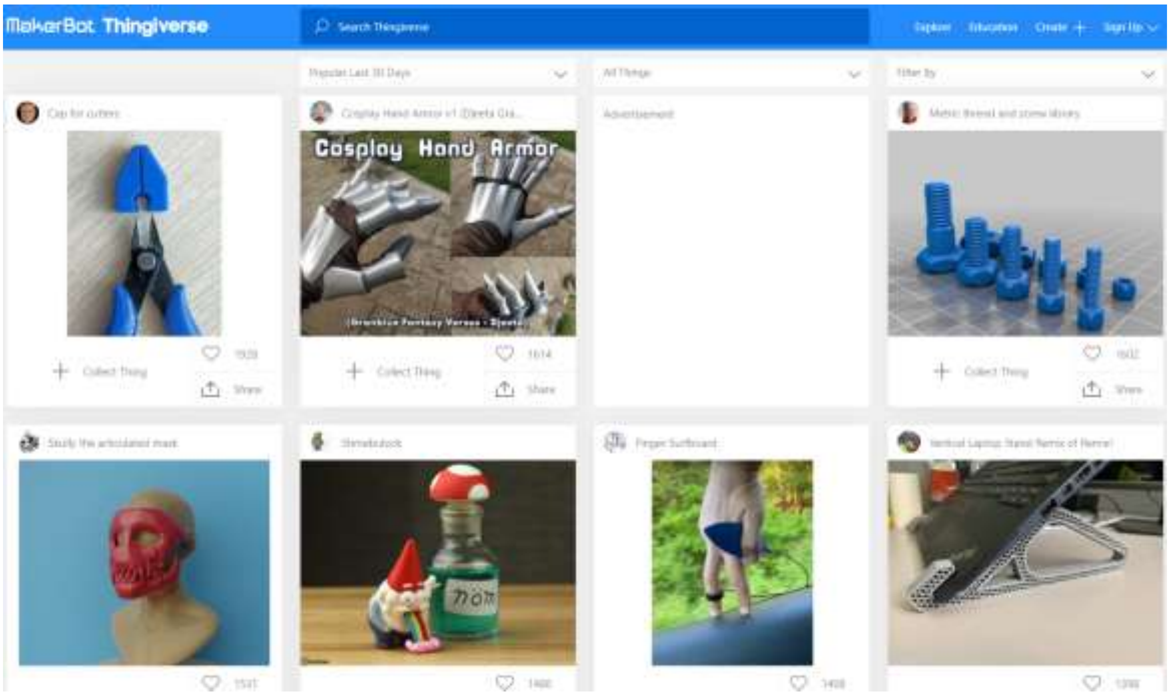

Figure 1: Thingiverse website's homepage

Data sampling

We collected only remixed ideas, including creator, posted date, user comments, category, images, text descriptions, files, likes, number of makes, and the origin information which include what ideas were remixed and its category. These data from Thingiverse were collected by using a custom-made web crawler implemented in python. The final dataset comprises 57,049 remixed ideas.

METHODOLOGY

Variables

Dependent variables

The dependent variable for the competing hypotheses is the *degree of innovation* of ideas. The number of forward citations of patents (i.e. the count of patents has been later patents) is frequently employed as a measure of the degree of innovation in research fields including knowledge-based innovation (Liu *et al*., 2020). The forward citation number is a crucial innovative indicator that reveals how often patents spur subsequent patents (Liu *et al*., 2020). Similarly, on Thingiverse, ideas can inspire the follow-up ideas which can be seen as the 'forward remixes.' Therefore, we used the *number of remixes* (i.e. how many ideas have been remixed by other ideas) as a proxy of the *degree of innovation*.

Additionally, we constructed another measurement of dependent variable, the *number of makes*. Ideas are generally accepted and implemented by people when the ideas are innovative (George & Zhou, 2007). We also considered the *number of makes* (i.e. the number of users who have actually printed the idea using a 3D printer) as a proxy of the *degree of innovation*. All dependent variables were log-transformed due to skewed distribution.

Independent variables

The first main independent variable is the *number of prior ideas*. We measured this by the *number of prior ideas* used for remixing. The prior ideas that have been combined for remixing are listed on Thingiverse.

The second main independent variable is a dummy variable representing whether the idea domains are transferred, denoted as *cross-boundary remix*. Each idea on Thingiverse has a category, which allows users to browse and search similar ideas. In this study, it is presupposed that if the category of an idea has changed, the domain of the idea has changed. Therefore, the *cross-boundary remix* is set to 1 if the category of the idea has changed (cross-boundary remix has occurred), and 0 otherwise.

We control for popularity indicators of ideas, such as likes and comments. The *likes* variable refers to the number of likes that indicate users' interest. The *comments* variable refers to the number of feedbacks of an idea. Then, we control for supplementary evidence of ideas such as the images and the idea length. *Images* variable refers to the number of images that provided by the idea publisher. The *idea length* variable refers to the count of words that were used to describe the idea. We control the complexity of ideas, such as files. The *files* variable refers to the number of files required to produce the idea to practice. In addition, the *published period*, which is calculated by the data collection date minus the idea published date, is used to control the period difference effect. The *category dummies* are used to control the intrinsic differences caused by different categories of ideas. Table 1 summarizes the descriptions of variables.

Table 1: Description and type of variables.

Variables	Description
Dependent variable	
Number of Remixes	The number of remixes that idea was remixed by other members
Number of Makes	The number of implementation that idea was implemented(printed) by other members
Independent variables	
Number of Prior ideas	The number of prior ideas used for remixing
Cross-boundary remix	1 if the idea remixed from different categories, 0 otherwise
Control variables	
Images	The number of images that provided by idea publisher
Idea Length	The number of words contained in the posted idea
Files	The number of files required to produce the idea
Comments	Number of comments on posted idea by members of the online community
Likes	The number of likes from members of the online community
Category	Category to which each idea belongs
Published Period	The period between the idea published date and the data collection date

Table 2: Descriptive statistics of continuous variables

	Num	Mean	SD	Min	Max
Number of Remixes	57,049	1.482	238.357	0	56,778
Number of Makes	57,049	0.425	7.572	0	1,309
Number of Prior ideas	57,049	1.092	0.639	1	27
Images	57,049	2.297	4.031	1	196
Idea Length	57,049	33.987	130.223	0	5,265
Files	57,049	1.767	6.208	0	1,278
Likes	57,049	32.286	370.336	0	51,761
Comments	57,049	1.290	14.886	0	2,185
Published Period	57,049	1,831.845	855.865	10	4,842

Descriptive Statistics and Correlations

Table 2 reports the descriptive statistics of all the variables. It is important to note that *cross-boundary remix* and *number of prior ideas* have a relatively low correlation in table 3. We produced variance inflation factors (VIFs), which measure the severity of multicollinearity in regression analyses, in order to test for possible issues of multicollinearity in our analyses. All VIFs were far below the 10 threshold (Cohen *et al*. 2014).

Empirical model

Since our dependent variables are continuous, we use the ordinary least squares estimator (OLS) to test our hypotheses. Equation (1) studies the impact of the *number of prior ideas* and *cross-boundary remix* on the *number of remixes* as a proxy of the *degree of innovation*. In equation (2), we used other dependent variables as mentioned in the dependent variables section. Therefore, we change the dependent variable, *number of remixes* to *number of makes*. The degree of innovation of remixed idea *i* can be written as

$$\begin{aligned} \textit{Number of Remixes}_i = \alpha &+ \beta_1\,(\textit{Number of Prior ideas}_i\,) + \beta_2\,(\textit{Number of Prior ideas}_i\,)^2 \\ &+ \beta_3\,(\textit{Cross-boundary remix}_i) + \gamma\ \textit{Controls}_i + \varepsilon_i \end{aligned} \tag{1}$$

$$\begin{aligned} \textit{Number of Makes}_i = \alpha &+ \beta_1\,(\textit{Number of Prior ideas}_i\,) + \beta_2\,(\textit{Number of Prior ideas}_i\,)^2 \\ &+ \beta_3\,(\textit{Cross-boundary remix}_i) + \gamma\ \textit{Controls}_i + \varepsilon_i \end{aligned} \tag{2}$$

Controls$_i$ represent a vector of control variables, including *images*, *idea length*, *files*, *comments*, *likes*, *published period*, and *category*. α is the constant term; ε_i is the error term; β_j can be interpreted as the change of degree of innovation when each variable change. γ is the vector of control variables' coefficient.

RESULTS

Main results

Table 4 presents the simple linear estimation results about the effect of the *number of prior ideas* on the *degree of innovation* and how the *cross-boundary remix* affects the *degree of innovation* of idea. Model (1) contains the *number of prior ideas* and its square term with control variables. Model (2) contains *cross-boundary remix* with control variables. Our main result is Model (3), which contains all independent variables. The adjusted R-squared value is 16.3% in Model (1) and it increases to 16.7%, and 16.8% in Model (2), and (3), respectively.

Table 3: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Number of Remixes										
(2) Number of Makes	0.04	1								
(3) Number of Prior ideas	-0.00	0.02*	1							
(4) Cross-boundary remix	0.01*	0.06*	0.09*	1						
(5) Images	0.04*	0.08*	0.15*	0.27*	1					
(6) Idea Length	0.00	0.04*	0.63*	0.18*	0.25*	1				
(7) Files	0.02*	0.03*	0.07*	0.09*	0.49*	0.10*	1			
(8) Comments	0.09*	0.74*	0.04*	0.07*	0.20*	0.13*	0.10*	1		
(9) Likes	0.07*	0.38*	0.04*	0.09*	0.16*	0.08*	0.06*	0.47*	1	
(10) Period	0.01	0.01*	-0.02*	-0.26*	-0.17*	-0.06*	-0.07*	-0.02*	-0.01	1

* Denotes significance at the 1% level.

Table 4: OLS estimation results using first dependent variable

	Dependent variable: *Number of Remixes*		
	Model (1)	Model (2)	Model (3)
Number of Prior ideas	0.046***		0.046***
	(3.71)		(3.83)
Number of Prior ideas^2	-0.003*		-0.003**
	(-2.56)		(-2.58)
Cross-boundary remix		0.072***	0.072***
		(10.38)	(10.28)
Images	0.011***	0.010***	0.010***
	(8.46)	(7.93)	(7.88)
Idea Length	0.000	0.000***	0.000
	(1.87)	(5.19)	(0.83)
Files	-0.006**	-0.000*	-0.000*
	(-2.95)	(-2.33)	(-2.30)
Comments	0.004***	0.004**	0.004**
	(3.30)	(3.26)	(3.28)
Likes	0.000**	0.000**	0.000**
	(3.07)	(3.06)	(3.05)
Published Period	0.000***	0.000***	0.000***
	(13.42)	(15.06)	(15.07)
Constant	-0.097***	-0.073***	-0.118***
	(-7.36)	(-12.59)	(-9.04)
Category Dummies	Included	Included	Included
N	57,049	57,049	57,049
adj. R^2	0.163	0.167	0.168
F	99.36	121.3	109.5

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: OLS estimation results using second dependent variable

	Dependent variable: *Number of Makes*		
	Model (4)	Model (5)	Model (6)
Number of Prior ideas	0.041***		0.041***
	(3.88)		(4.17)
Number of Prior ideas^2	-0.004***		-0.004***
	(-4.93)		(-5.41)
Cross-boundary remix		0.163***	0.162***
		(17.10)	(16.95)
Images	0.018***	0.016***	0.016***
	(7.77)	(7.39)	(7.37)
Idea Length	0.000*	0.000	0.000
	(2.44)	(0.95)	(0.12)
Files	-0.003	-0.003	-0.002
	(-1.56)	(-1.52)	(-1.52)
Comments	0.003**	0.003**	0.003**
	(3.22)	(3.19)	(3.20)
Likes	0.000**	0.000**	0.000**
	(3.12)	(3.13)	(3.12)
Published Period	0.000***	0.000***	0.000***
	(14.42)	(18.25)	(18.31)
Constant	-0.077***	-0.083***	-0.122***
	(-6.81)	(-11.84)	(-11.28)
Category Dummies	Included	Included	Included
N	57,049	57,049	57,049
adj. R^2	27.91%	29.48%	29.60%
F	155.5	232.7	208.3

p-values in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The *number of prior ideas* and the *degree of innovation of idea* have a significant inverted U-shaped relationship. (Model 3: $\beta_{prior\ ideas} = .046$, $p < 0.001$; $\beta_{prior\ ideas^2} = -.003$, $p < 0.05$); thus, Hypothesis 1 is supported. Using some proper prior idea has a positive effect on the *degree of innovation*, but using more ideas than a certain level has a negative effect on the *degree of innovation*.

Cross-boundary remix is positively correlated with the *degree of innovation* (Model 3: $\beta_{cross\text{-}boundary\ remix} = .072$, $p < 0.001$), so Hypothesis 2 is supported. Ideas remixed from the heterogeneous domain idea have a positive effect on the *degree of innovation*.

To validate our estimation results, in Tables 5, we further explore our hypotheses by using another dependent variable, *number of makes*. This alternative dependent variable is important because the degree of innovation has been measured as not only inspiring follow-up subsequent innovation but also measured innovation as idea's implementation. The results using alternative dependent variable show consistency with the main results. Model (4), (5), and (6) shows that the *number of prior ideas* and the *cross-boundary remix* significantly effect and have similar trend with main results on the *degree of innovation*.

CONCLUSIONS

Discussion of Findings

This study aims to investigate the impact of cross-boundary remixes and the number of prior ideas on the degree of inventiveness of ideas in OICs. Our results reveal that there is an inverted U-shaped relationship between the number of prior ideas used for remixing and the degree of innovation of the idea. The more prior ideas used for remixing, the more innovation of the idea increases, but after a certain point the degree of innovation decreases. We also find that cross-boundary remix increases the idea's degree of innovation. Ideas that were remixed from different domains are more innovative than ideas that were remixed from the same domain. These results showed the same phenomena for two independent variables (*number of remixes* and *number of makes*).

Theoretical Implications

We suggest three theoretical contributions. First, our study found how remixing creates more innovative ideas in the OICs. Since there are few studies that have confirmed remixing on online platforms, this study can be said to be a new attempt, unlike other studies. Second, our study collected data through a new platform called Thingiverse, one of the OICs. This suggests that OICs with new characteristics continue to appear in our society, and shows that platform-specific characteristics are prominent. As a result, this study can be said to be a timely study for platform changes. Third, the results of this study show the form of an inverted U-shaped, and it was found that too much remixing reduces the number of ideas generated. This provides implications that too much innovation within the OICs has adverse effects.

Managerial Implications

From the perspective of channel operators who operate OICs, they can understand how to create efficient ideas. First, in the case of channels that do not use remixing as a category among OICs, it is possible to consider expanding channel operations by classifying remixing into categories. This improves users' innovation and helps them share new ideas. Second, as a result of this study, since an inverted U-shaped has occurred, it is important to understand where the OICs is refracted. Through these inflection points, various countermeasures such as not showing the remix number in detail can be discussed. Third, since innovation helps create ideas, it can be considered to add categories that can increase innovation. In this paper, innovation is viewed as a remix, so other factors besides remixing can be introduced.

Limitations and Future Research

The study that we conducted is subject to a few limitations. First, we examined only one OICs. It is possible that other OICs will bring results that contradict our findings. Therefore, it will be limited to generalizing our findings. Second, we gathered our dataset at one particular moment in time, representing a snapshot of a vibrant platform. For example, we simply know the number of makes at a given point in time. There is no record of when a download occurred. Therefore, our dataset does not provide an explanation of the complex causality involved in innovation. Third, our study only relies on data from the OICs itself. Our study did not include interviews with users and consideration of their motivations. It would be helpful to comprehend their motivation regarding the effect of the number of recombined prior ideas and cross-boundary remix on the degree of innovation of the idea in OICs.

Thus, we recommend that future studies consider various OICs as a dataset. The more dataset from various platforms enhanced the validity of generalizing the research findings. Moreover, to overcome the nature of the dataset as a snapshot and to gain the causality involved in innovation, future research should consider interviews with users. It would help to find various factors affecting the degree of innovation of ideas in OICs.

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