7-8-2023

The Impact and Evolution of Individual’s Learning: An Empirical Study in Open Innovation Community

Mengyuan Wang
HuaZhong University of Science and Technology, m202274212@hust.edu.cn

Jifeng Ma
HuaZhong University of Science and Technology, 821264251@qq.com

Yaobin Lu
HuaZhong University of Science and Technology, luyb@hust.edu.cn

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Completed Research Paper

Mengyuan Wang
Huazhong University of Science and Technology, Wuhan, China
wangmengyuan_@hust.edu.cn

Jifeng Ma
Wuhan Textile University, Wuhan, China
821264251@qq.com

Yaobin Lu
Huazhong University of Science and Technology
Wuhan, China
luyb@hust.edu.cn

Abstract

Learning is critical for individuals to increase their performance. However, this benefit of learning is not always realized. Previous studies have distinguished different classifications of learning approaches and reached inconsistent results. Therefore, this study further refines the classification of learning approaches in an open innovation community and explore the individual's learning curve from a dynamic perspective. Specifically, we focus on whether and under what conditions learning can increase individual's performance, and how individual's learning curve changes over the tenure. To examine our hypotheses, we collect a dataset includes 48,820 game mods developed by 6,141 creators spanning 7-years from an open game innovation community. The results not only show the significant curve relationship between the four learning approaches and performance, but also demonstrate individual's learning curve evolves over the tenure. This paper provides valuable suggestions and implications for individuals to choose appropriate learning approaches and obtain better performance under different tenures.

Keywords: learning approaches, active and passive learning, learning from own and others, learning curve, dynamic perspective

Introduction

Learning is the fuel for individuals to start their engines of obtaining new knowledge(Bolisani and Bratianu 2017). With the accumulation of learning activities, individuals are more likely to achieve a high performance because these learning activities enable them to embrace diverse perspectives and possess unique abilities(Boone et al. 2008; Mukhopadhyay et al. 2011). However, this assumption of "the more, the better" has been challenged in recent research as scholars do not always empirically demonstrate the positive effect of learning(Kim et al. 2012; Yang et al. 2021). For example, Zollo(2009) found that superstitious learning, which refers that individuals cannot accurately judge the connection between actions and outcomes when they learn from prior experience, can hurt individual's future performance. Thus, identifying a better learning strategy and increasing the learning efficiency is critical to achieve the benefit of learning on individual's performance.

To understand the effect of learning more clearly, many scholars have tried to distinguish various learning approaches and examine their differential effects on performance. For example, prior studies have outlined two approaches of learning based on the learning sources: learning from own, which refers to directly learning by the consequence of actual doing, and learning from others, which refers to indirectly learning by watching others' performance (Gino et al. 2010; Shi et al. 2021). Similarly, prior studies have also distinguished two learning approaches based on the learning styles: active learning, which means that individuals are initiators of learning activities and consciously search knowledge, and passive learning, which means that individuals are receptors of knowledge and passively gain knowledge through learning activities initiated by externals (Dahlander and Piezunka 2014). However, there are several gaps of these research on individual's learning. First, the results on the impact of learning are still mixed. For instance, various studies of learning from own have found positive, negative, and non-significant effect on individual's performance(Amore et al. 2021; Deichmann and Ende 2014; Ellis and Davidi 2005). Second, although social context plays an important role in examining the effect of learning, most studies have been conducted in the offline context, such as organizational context(Madsen and Desai 2010; Wilhelm et al. 2019). Comparing with offline context, online context has a higher level of media richness that can provide more choices for individuals to select how to engage in learning activities. Furthermore, individual's learning activities can be easily recorded in online context and these objective data are valuable in understanding the effect of learning. Third, learning is a dynamic process because the ability of absorbing and synergizing new knowledge evolves with the development of individual's cognitive structure (Mannucci and Yong 2018). Therefore, it is important to figure out how the relationship between individual's learning and performance changes over the time.

Thus, we put forward the following research questions: *(1)Whether and under what conditions can learning increase individuals' performance in the context of open innovation community? (2)How does the impact of individual's learning evolve over the individual's tenure?*

Based on our research questions, our study further refines individual's learning approaches in the context of open innovation community, that is, to divide learning approaches into active learning from own, active learning from others, passive learning from own, and passive learning from others, so as to explore the relationship between individual's learning and performance. In addition, we also examine how the impact of individual's learning evolves over the individual's tenure. We collect a rich dataset that includes 48,820 game mods developed by 6,141 creators spanning 7-years from an online game open innovation community. Our empirical results prove that there is a significant curvilinear relationship between the four learning approaches and performance, and demonstrate the evolution of the learning curve under different individual's tenure.

Literature Review

Learning Approaches

Active Learning and Passive Learning

In terms of the classification of learning styles, learning is mainly divided into single cycle learning through passively receiving information, double cycle learning and second learning through active and creative learning(Dodgson 1993). Deci et al. (1987) also believe that individual behaviors are either active behaviors initiated through their own independent choices or passive behaviors initiated through external demands.

On the one hand, at the enterprise level, Li et al.(2013) take the interactive memory system as a prerequisite for enterprise learning, and the results show that the active learning and passive learning are both positively correlated with project performance. But Yang et al.(2021) prove that active learning and passive learning have opposite effects on performance. However, Li et al.(2010) identify that active learning and passive learning are incompatible, and the two learning styles have an inverted U-shaped curve influence on the performance of new products.

On the other hand, at the individual level, Mom et al.(2009) explore the impact of an individual's knowledge inflow on active and passive learning; Lee et al.(2017) study the influence of incentives on individuals' active and passive learning behaviors. Stillesjö et al.(2021) prove that active learning is crucial to promoting good long-term memory. As for the relationship between individual active or passive learning and their performance, Hong et al.(2018) show that the individual allocation of active and passive learning can produce the highest individual performance under certain conditions. Gregory et al.(2006) think that active learning has a better grasp of knowledge than passive learning. Shi et al.(2021) find that active learning significantly influence the user's informativeness of future contributions. In crowdsourcing contest, Jin et al.(2021) show that high quality knowledge sharing as an active learning method has a significant positive impact on players' performance. The study by James et al.(2002) also argues that active learning performs better than passive learning. However, Qiu et al.(2020) find that there is no significant difference in the performance of active learning group and passive learning group through the experimental study. In addition, the research of Cao et al.(2019) reach the opposite conclusion to the above research, that is, passive learning is more effective than active learning.

The conclusions of previous research on the impact of active learning and passive learning on performance are not consistent no matter at the enterprise level or individual level. Besides, there has been no research on the combination of these two learning styles and learning source to achieve a more detailed classification of learning and thus reveal the impact of different learning approaches on performance, so it is worth noting that the two are combined to carry out research.

Learning from Own and Learning from Others

The social learning theory proposed by Bandura focuses on the role of observational learning and self-regulation in triggering human behavior, attaches importance to the interaction between human behavior and environment, and emphasizes the role of observational learning in acquiring human behavior(Bandura 1977). Based on social learning theory, Bandura then proposes social cognitive theory, which holds that there are two main objects to learn, one is to learn through the results of one's own actions, another is to learn through observing the performance of others(Gupta and Bostrom 2012).

Organizations and individuals learn directly from their own experiences and indirectly from the experiences of others(Levitt and March 1988). Indirect learning from the experiences of others is valuable because it provides knowledge that individuals or organizations cannot obtain directly(Gino et al. 2010). The research of Christoph et al. indicates that people constantly improve their own performance by observing others' good examples(Riedl and Seidel 2018). In learning through direct and indirect experience, individuals learn more from their own successes than from their own failures, but they learn more from the failures of others than from the successes of others(Kc et al. 2013; Aggarwal et al. 2021). In different learning states, the importance of different learning approaches to individuals is not consistent. Regardless of learning status, learning from others seems to be the most important source of learning; In the medium learning state, individuals rely more on learning from their own experience, while in the high and low learning states, individuals learn more from others, and in the low learning state, individuals rely entirely on learning from others(Singh et al. 2011).

Dynamic Effects of Leaning

March(1991) explores the effectiveness of active learning and passive learning at different times: passive learning may be more effective in the short run, while active learning is more effective for the performance in the long run. In research work, experienced researchers who have been active in a particular field for a longer period of time have more opportunities to interact and learn from industry researchers than those who are early in their careers(Aschhoff and Grimpe 2014). Mustapha et al.(2018) show that the relationship between learning from others as measured by the degree of collaboration between the scholar and external collaborators, and the impact of the scholar's research, depends on scholars' career age. However, the moderating effect of tenure on learning approaches and performance has rarely been mentioned in the research, and the previous studies hardly explored the change of learning curve with tenure. Therefore, it is necessary to study how the impact of various types of learning approaches on performance changes in different periods.

Theory Development and Hypotheses

From the perspective of classification of learning, this study further subdivides learning approaches into four types: active learning from own, active learning from others, passive learning from own, and passive learning from others. We argue that different learning approaches can have different effects on performance.

In addition, we discuss the impact of the tenure on one's learning curve. We propose that the relationship between learning approaches and performance can be mediated by tenure. Figure 1 summarizes the research model and presents the hypotheses in the following sections.

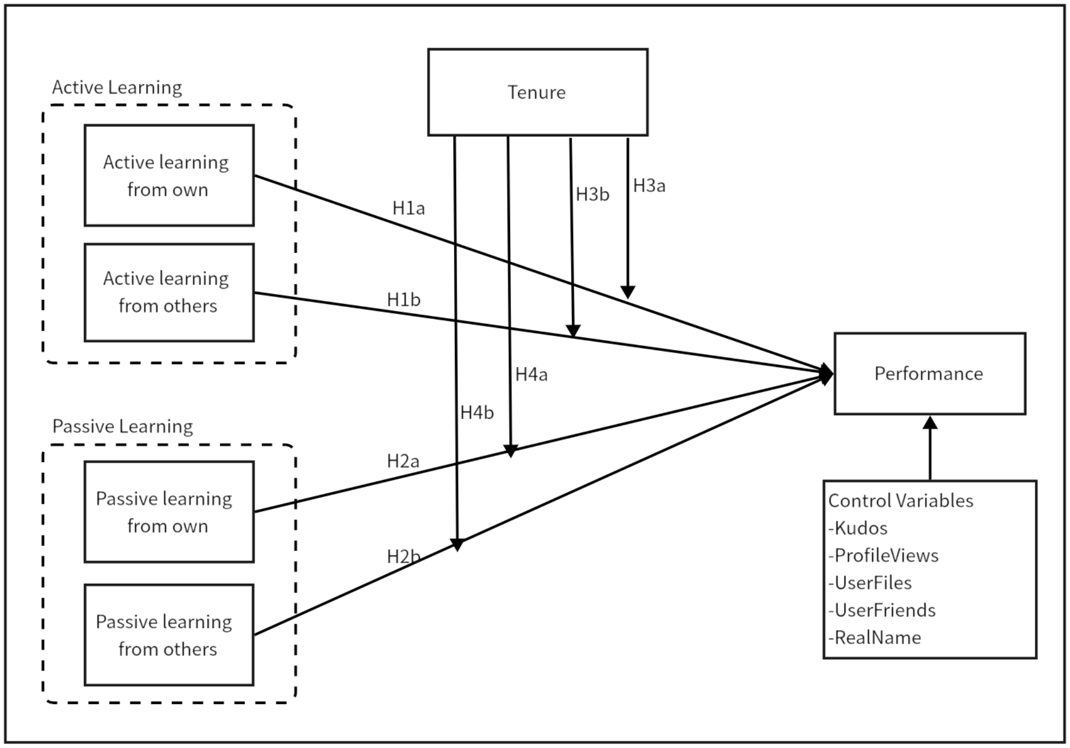


Figure 1. Research Model

The Impact of Active Learning on Performance

Active learning is a self-directed process, characterized by high levels of individual willingness and motivation to learn. Increased passion for learning makes individuals get more satisfaction from learning, thereby promoting continued engagement in the learning process. Besides, individuals tend to initiate their learning process in familiar domains. Subsequently, we will integrate active learning with learning from own and learning from others for further discussion.

On the one hand, active learning from own is a learning process through improving their works characterized by their own willingness. Because learning from own means the degree of overlap between the learned knowledge and the individual's existing knowledge is high, which leads to the internalization speed of knowledge is fast, but the conversion rate is not high. That is, due to the high similarity and overlap between the knowledge learning from own actively and individual’s exiting knowledge, the knowledge that really pals a role is limited and the conversion rate of knowledge is low, so that individual’s performance declines. However, as the degree of active learning from own deepens, the willingness of learning is higher and the ability of digging new insights through similar knowledge becomes higher, so the conversion rate of knowledge increased. Besides, individuals’ works become more perfect through the process of improving their works, so their performance would increase. Therefore, we propose the following hypothesis:

Hypothesis 1a: Active learning from own and individual's performance have a U-shaped relationship.

On the other hand, active learning from others is the process of learning from others’ works by their own willingness. Likewise, active learning from others is also a kind of active learning, which means individuals always tend to start with others’ works that are familiar to their own domains. So it would also occur the problem of the internalization speed is high while the conversion rate of knowledge is low, which also leads to the really useful knowledge is little and the performance declines. However, with the degree of active learning from others deepen, as the knowledge structure and interest domain of different individual is not always literally the same, the deeper degree of active learning from others makes individuals contact to more different kind of knowledge from others, which broadens individuals' knowledge structure and helps to spread their thinking and combine them to their existing knowledge. Based on this, individuals can propose more interesting and popular ideas that helps to increase their performance. Therefore, we propose the following hypothesis:

Hypothesis 1b: Active learning from others and individual's performance have a U-shaped relationship.

The Impact of Passive Learning on Performance

Compared to active learning, passive learning is the process in which individuals are forced to receive knowledge, so the learning willingness of passive learning is lower. Since passive learning is receiving knowledge without subjective motivation, as the degree of passive learning deepens, inertia and lower learning ability will occur to individuals. Next, we will further discuss by combining passive learning with learning from own and learning from others.

On the one hand, passive learning from own is the process of individuals accept their prior works' performance passively, which means individuals are forced to accept whether their prior works perform well or not well and learn from them. Individuals could pick up some of the popular and unpopular qualities of their past works and apply them to their subsequent works in this process, and it makes their works more suitable for users' preferences and thus improve their performance. However, as the degree of passive learning from own deepens, individuals may rely on accept knowledge passively which leads to inertia and decrease the learning ability, and due to the indulge in their past experience to produce new works, the scope of individual learning is narrow and limited, and leads to the decline of performance. Thus we hypothesize:

Hypothesis 2a: Passive learning from own and individual's performance have an inverted U-shaped relationship.

On the other hand, passive learning from others is the process of individuals have to solve the problems raised by others and learn from them. Since the problems raised by others are not always in the areas of individuals' familiarity and expertise, individuals could broaden their knowledge width and diversity through learning from others, and make more interesting works. Besides, in the process of solving other users' problems, users' needs are met and the quality of the work is improved, so the performance increases. However, as the degree of passive learning from others deepens, individuals are accustomed and addicted to propose new works from the ideas raised by others, which decreases their ability of learning and the internalization of knowledge. As Narver et al.(2004) point out that a business that learns and develops new products by completely relying on the needs expressed by customers creates no new insights into value-adding opportunities for the customer and thereby creates little or no customer dependence and foundation for customer loyalty. Therefore, we propose the following hypothesis:

Hypothesis 2b: Passive learning from others and individual's performance have an inverted U-shaped relationship.

The Moderating Effects of Tenure on Learning

Another important factor in explaining the impact of individuals' learning curve is tenure, which is the total time each individual joins the community. For active learning, active learning itself is a learning process with high willingness to learn, but the learning willingness will change as the tenure increases. Generally speaking, the newcomers are always more curious, so the individual whose tenure is low would have higher active learning willingness. By contrast, the old hands are more likely to develop path dependence, which means the individuals with higher tenure will have lower active learning willingness. So we believe that the effect of active learning decreases as the increasing of tenure, due to the willingness to learn decreases with tenure. Therefore, the active learning curve gets flatter as the tenure increases. Then, for the curves' changes of active learning from own and active learning from others, we propose the following hypotheses:

Hypothesis 3a: The curve of active learning from own would get flatter as the tenure increases.

Hypothesis 3b: The curve of active learning from others would get flatter as the tenure increases.

For passive learning, passive learning itself is a learning process with low willingness to learn. But we believe that individuals' ability to internalize knowledge improves as the increasing of tenure, that is, individuals with higher tenure are better able to decide what knowledge is more beneficial to them and use that knowledge from passive learning more effectively. Therefore, with the increase of tenure, whether passive learning from own or passive learning from others, individuals could more quickly extract the knowledge that is more conducive to their performance from the knowledge passively acquired from themselves and others. Hence, we believe that the passive learning curve would reverses in a U-shape as the tenure increases. Therefore, we propose the following hypotheses:

Hypothesis 4a: The curve of passive learning from own would reverses in a U-shape as the tenure increases.

Hypothesis 4b: The curve of passive learning from others would reverses in a U-shape as the tenure increases.

Research Method

The Research Context

In order to test the hypotheses of the research model, we focus on the online mod innovation community NexusMods (www.nexusmods.com), a virtual community where users voluntarily upload game modules created by themselves. NexusMods is the world's largest and most engaged virtual community of user-uploaded game modules. By the end of 2022, the website had 166,620 users uploading 430,576 game module files under 2,036 games, and the website had more than 38 million registered people and more than 7 billion downloads.

In NexusMods, it not only provides a complete mod manager and code library, but also provides general modding tutorials and commonly used tools for the creators. In the community, users can create and upload one or more works of their own, known as game mods, and the detailed introduction of the works, the reviews and feedback will be displayed on the page of their works. After the game mod has been uploaded, other users could view and download the mod, and choose whether to give it a "like", which is called "Endorsements" in the community. If other users find bugs while playing the current mod, they can also send feedback to the creator through the "Bugs" module of the current mod page. Besides, after uploading the work, the creators can carry out additional updates by themselves, such as adding different versions suitable for different devices, or adding new content based on the current mod, and upload it to the webpage of the current work in the form of files through the "Files" module of the current mod page. In addition, the detailed activities of each user in the community are recorded on their personal page. It includes the total number of mods uploaded by users (User Files), the number of times and time of endorsements given by users to mods uploaded by others (Endorsements given), the number of user's friends (Friends), the number of likes (Kudos) and the number of views (Profile views) received by users' personal pages, as well as users' personal information, such as real name, country, and when they joined the community (Join date) and so on.

There are several reasons for choosing NexusMods as our research model. First of all, NexusMods is a community where the quality of the uploaded work is judged by all users, with no interference from the platform or game side. Secondly, the community has detailed evaluation indicators and modules for users' uploaded works, which enables us to quantify independent variables in our study. In addition, users in the community have personal website pages, this gives us a wealth of information to control for more individual characteristics in our model.

Sample and Data Collection

We focused on all the game mods uploaded by all users for a certain game in the community. The game is a role-playing adventure game that has won many awards in the game field. At the same time, the game has an open game setting and a high degree of freedom of the mod setting, that is to say, the game players can create and design the mods they like very freely, and add them to the game, so the users in the mod community of the game are very active. Figure 2 shows a screenshot of the first page of a work uploaded by a user in the game community.

In the NexusMods game community, the first game was uploaded by a user on November 6, 2015. We used Python crawler to obtain detailed data of all the creators and works uploaded by all the creators in the game community up to the end of December 2022. These user-uploaded works involve about 800 games, so it is fairly representative. A total of 90,052 works uploaded by 42,997 users in the game community were collected. After deleting invalid data and data that did not meet the conditions of our model, 48,820 valid data were left for testing.

Variables

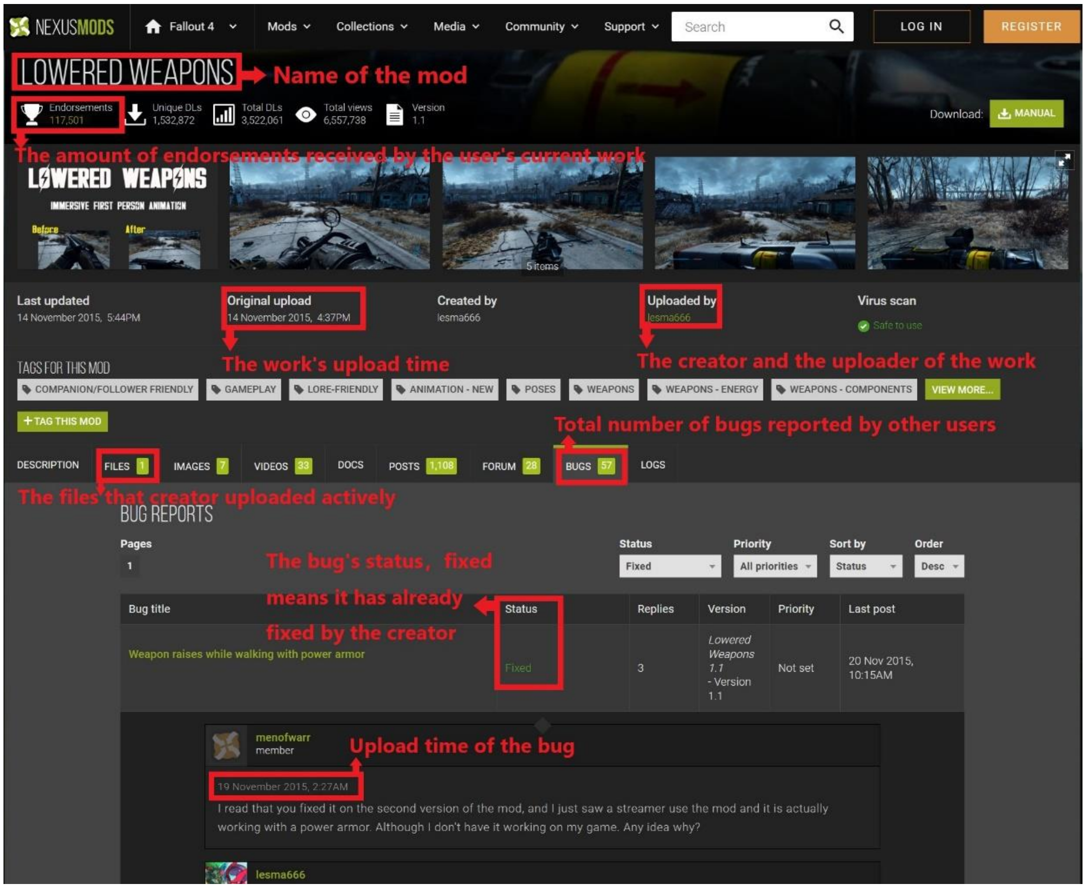


Figure 2. A screenshot of the first page of a work

The dependent variable in this study is the performance of an individual's work, that is, the amount of endorsement the work received. In the community, players can choose whether to endorse a game only after downloading it, and each user account can only endorse the same work once. In addition, in the Mods section on the NexusMods homepage, users can choose to browse all the games in order of endorsement from highest to lowest by the “most endorsed” option. Therefore, the endorsement a work receives is an important way to measure its performance.

The independent variables are the four learning approaches of users: active learning from own, active learning from others, passive learning from own, and passive learning from others. First of all, users create and upload files through the "Files" module of the current mod page not under external pressure, but out of their own passion and hobbies actively. Meanwhile, the files uploaded by users are created based on their published works, which is to learn and update their own works from their past experience. Shi et al.(2021) take learning from their own past experiences as a measure of learning from own. Therefore, we use the cumulative number of files uploaded in all previous works of the creator's current work as a measure of the user's active learning from own. Secondly, Singh et al.(Singh et al. 2011) measure learning from others in their study by reading the cumulative number of threads started by others; Aggarwal et al.(2021) also measure learning from others by interacting with other participants to acquire knowledge. However, in this community, users can choose whether to endorse a work only after downloading and experiencing it, so the premise of endorse the work is to experience the work. At the same time, user experience and endorsing others' works are active processes that are not affected by the outside world. Therefore, we measure active learning from others by the total number of endorsements that a creator has accumulated given to others' works prior to the upload of his/her current work.

Thirdly, Dahlander et al.(2014) measure passive learning by measuring the number of suggestions from external contributors that organizations focus on; Lindberg et al.(2022) use the quality of an individual's previous creative ideas as an assessment of learning from own. The amount of endorsement received by a creator's past works is the indicator that individuals can only accept it passively but cannot change it, which can be regarded as passive learning by analogy with Dahlander et al. 's measurement method. At the same time, the amount of endorsement obtained by the creator's past works is also the quality of creator's past works. Therefore, we measure passive learning from own by the cumulative amount of endorsement received by all previous works of the creator's current work. Finally, Au et al.(2009) measure learning effects using the number of resolved bugs in the project. In this community, creators are forced to passively fix the bugs and learn from the bugs reported by others. Therefore, we measure passive learning from others by the cumulative number of fixed bugs of user's previous works.

The control variables in this paper include kudos and the total views the creator obtained on his/her profile, the works uploaded by the creator totally, the number of friends that the creator has, and whether the creator leaves out his/her real name on the profile which is a dummy variable. Table 1 provides the description of the variables in our study. Table 2 shows the descriptive statistics.

Table 1. Variable Description

Type	Variable	Description	References
Independent Variables	Active learning from own (ALO)	We measure this by the cumulative number of files that the creator actively uploaded for all his/her works prior to the current work.	(Shi et al. 2021)
	Active learning from others (ALOT)	We measure this by the cumulative number of endorsements the creator has given to other user's works for all his/her works prior to the current work.	(Singh et al. 2011)
	Passive learning from own (PLO)	We measure this as the cumulative number of endorsements that the creator has received for all his/her works prior to the current work.	(Lindberg et al. 2022; Dahlander and Piezunka 2014)
	Passive learning from others (PLOT)	We measure this as the cumulative number of bugs fixed by the creator in all works prior to his/her current work.	(Au et al. 2009)
Moderator	Tenure	The number of years between the creator's registration in the	(Zhang et al. 2009)

		community and the release of the current work.	
Control Variables	Kudos	The number of likes received by the creator's homepage.	(Ma et al. 2019)
	ProfileViews	The number of views of the creator's home page.	(Scott and Hand 2016)
	UserFiles	The total number of works uploaded by the creator.	(Jensen et al. 2014)
	UserFriends	The number of friends a creator has.	(Tong et al. 2008)
	RealName	Whether the creator discloses his/her real name on his/her home page, which is a dummy variable.	(Tominaga et al. 2018)
Dependent Variable	Performance	The amount of endorsements received by the creator's current work.	(Li et al. 2016)

Model Estimation

To test our hypotheses regarding the four learning approaches and the moderating effect of tenure on the performance, we employ the following empirical model. Since the dependent variables are all non-negative integers, we employ a negative binomial regression model. At the same time, in order to unify the data dimension, we standardize all the independent variables, moderating variables and control variables. The model is shown as follows:

$$\begin{aligned} Performance_{i,j} = {} & \beta_0 + \beta_1 \cdot ControlVariables + \beta_2 \cdot ALO_{i,j} + \beta_3 \cdot ALOT_{i,j} + \beta_4 \cdot PLO_{i,j} + \beta_5 \cdot PLOT_{i,j} + \beta_6 \\ & \cdot ALO_{i,j}^2 + \beta_7 \cdot ALOT_{i,j}^2 + \beta_8 \cdot PLO_{i,j}^2 + \beta_9 \cdot PLOT_{i,j}^2 + \beta_{10} \cdot Tenure_{i,j} + \beta_{11} \cdot Tenure_{i,j} \cdot ALO_{i,j} \\ & + \beta_{12} \cdot Tenure_{i,j} \cdot ALOT_{i,j} + \beta_{13} \cdot Tenure_{i,j} \cdot PLO_{i,j} + \beta_{14} \cdot Tenure_{i,j} \cdot PLOT_{i,j} + \beta_{15} \\ & \cdot Tenure_{i,j} \cdot ALO_{i,j}^2 + \beta_{16} \cdot Tenure_{i,j} \cdot ALOT_{i,j}^2 + \beta_{17} \cdot Tenure_{i,j} \cdot PLO_{i,j}^2 + \beta_{18} \cdot Tenure_{i,j} \\ & \cdot PLOT_{i,j}^2 + \varepsilon_{i,j} \end{aligned}$$

Let $i = 1 \dots N$ index the user, $j = 1 \dots M$ denote the $j\ th$ work of user i. Where $\varepsilon_{i,j}$ is the error term. And β_2 to β_9 are the parameters to be estimated, β_{10} to β_{18} are the parameters for testing the moderating effect.

Table 2. Descriptive statistics and Correlation (N=48,820)

Variables	Mean	Std. Dev.	(1)	(2)	(3)	(4)
(1)Performance	576.998	5,466	1			
(2)ALO	49.217	103	-0.011	1		
(3)ALOT	54.393	261	-0.010	0.058	1	
(4)PLO	17,389	101,676	0.097	0.305	-0.007	1
(5)PLOT	2.330	9	0.002	0.337	0.014	0.233
(6)Tenure	1944.684	1,365	-0.009	0.324	0.083	0.114
(7)Kudos	227.052	601	0.159	0.332	0.034	0.329

(8)ProfileViews	44437.190	124,519	0.138	0.317	0.032	0.324	
(9)UserFiles	53.722	77	-0.007	0.706	-0.001	0.277	
(10)UserFriends	80.458	357	0.120	0.199	0.031	0.221	
(11)RealName	0.545	0	-0.005	0.194	0.015	0.074	
	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(5)PLOT	1						
(6)Tenure	0.261	1					
(7)Kudos	0.208	0.164	1				
(8)ProfileViews	0.222	0.151	0.868	1			
(9)UserFiles	0.229	0.226	0.296	0.299	1		
(10)UserFriends	0.077	0.089	0.808	0.535	0.168	1	
(11)RealName	0.072	0.096	0.100	0.087	0.265	0.076	1

Results

Model Estimation Results

We present our model hierarchically, we first add only control variables in the model 1, and then introduce independent variables and squared terms in model 2 and the interaction terms in model 3. Because the VIF (variance inflation factor) statistics for all the independent variables are smaller than 3, we exclude the problem of multicollinearity. In addition, we used the robust regression model in Stata software, that is, robust standard errors were used for the significance test. Therefore, the estimation results are robust regardless of the presence of heteroscedasticity problems. Tables 3 present the results of robust negative binomial regressions.

Table 3. Model estimation results

Performance	Model 1 (Control)	Model 2 (Independent)	Model 3 (Total)
Constant	5.867**(0.038)	5.763***(0.000)	5.827***(0.000)
Kudos	1.812(0.186)	1.654***(0.000)	-0.426***(0.000)
ProfileViews	0.242(0.212)	-0.277*(0.015)	-0.367***(0.000)
UserFiles	-0.578**(0.040)	-0.398***(0.001)	1.792***(0.000)
UserFriends	-0.766*(0.091)	-0.558***(0.000)	-0.560***(0.000)
RealName	-0.052**(0.027)	-0.041(0.107)	-0.038(0.132)
ALO		-0.765***(0.000)	-0.936***(0.000)
ALO^2		0.081***(0.000)	0.152***(0.000)
ALOT		-0.164**(0.000)	-0.170***(0.000)
ALOT^2		0.006***(0.000)	0.009**(0.004)
PLO		1.684***(0.000)	2.668***(0.000)
PLO^2		-0.116***(0.000)	-0.213***(0.000)
PLOT		-0.028(0.439)	0.173***(0.000)

PLOT^2		-0.005(0.106)	-0.037***(0.000)
Tenure			-0.248***(0.000)
Tenure*ALO			0.148***(0.000)
Tenure*ALO^2			-0.044***(0.000)
Tenure*ALOT			0.034(0.326)
Tenure*ALOT^2			-0.004(0.058)
Tenure*PLO			-1.291***(0.000)
Tenure*PLO^2			0.119***(0.000)
Tenure*PLOT			-0.099**(0.002)
Tenure*PLOT^2			0.021***(0.000)
Wald χ^2	1,296.44(***)	3,682.15(***)	4,821.52(***)
N	48,820	48,820	48,820
Log pseudolikelihood	-308,386.53	-305,927.81	-304,997.3

***p<0.001, **p<0.01, *p<0.05 (Robust standard errors in parentheses)

According to the results of Model 2 and Model 3, both active learning from own and active learning from others have a significant U-shaped relationship with performance. This supports Hypotheses 1a and 1b. The relationship between passive learning from own and performance is a significant inverted U-shaped relationship in both models 2 and 3, which supports Hypothesis 2a. However, the inverted U-shaped relationship between passive learning from others and performance is not significant in Model 2, but is significant in Model 3, so we believe that Hypothesis 2b is also supported.

Model 3 reports the results of the full model including the moderating effect. The linear effect from active learning from own to the performance is negative and significant ($\beta=-0.936$, $p<0.001$), whereas its squared effect is positive and significant ($\beta=0.152$, $p<0.001$). The interaction between tenure and active learning from own is positive, and the interaction between tenure and active learning from own squared is negative ($\beta=-0.044$, $p<0.001$). This result supports Hypothesis 3a, which states that the relationship between active learning from own and performance depends on tenure. Similarly, according to the coefficients of each interaction term in Model 3, hypothesis 4a and 4b are also supported.

Robust Check

To make sure that our results are robust, we conduct the robust check by using alternative measurement of our variables. We replace the measurement of dependent variable from the work's endorsements to the number of unique downloads of the work. Unique downloads refer to the number of people who downloaded the work, excluding the number of times a single person downloaded a work repeatedly. We believe that the higher the work's unique downloads, to some extent, the more popular the work is, the better it performs, and the more attractive it is for users to download the work. The results are shown in Table 4 using robust negative binomial regression with the dependent variable measured by unique downloads.

Compared with the original results, although the robust check results show that the coefficients of ALOT and ALOT^2 are not significant. The coefficients of ALOT in original result and robust check result are both negative, and the coefficients of ALOT^2 in original result and robust check result are both positive. In addition, the significance of other independent variables and moderating effect are consistent with the original model. So we believe that our results are robust.

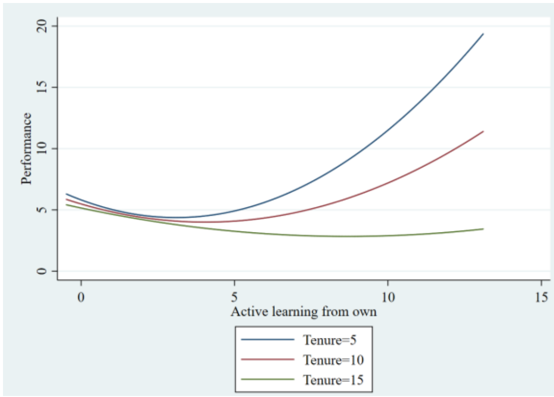
Table 4. Robust check results

Performance	Coef.	Std. Err.	P>z
Constant	8.700	0.030	0.000
Kudos	1.710	0.119	0.000
ProfileViews	-0.325	0.054	0.000
UserFiles	-0.442	0.100	0.000
UserFriends	-0.657	0.119	0.000
RealName	-0.040	0.021	0.058
ALO	-0.731	0.156	0.000
ALO^2	0.127	0.019	0.000
ALOT	-0.048	0.037	0.197
ALOT^2	0.002	0.002	0.242
PLO	2.191	0.209	0.000
PLO^2	-0.176	0.018	0.000
PLOT	0.499	0.045	0.000
PLOT^2	-0.065	0.007	0.000
Tenure	-0.138	0.025	0.000
Tenure*ALO	0.142	0.022	0.000
Tenure*ALO^2	-0.044	0.005	0.00
Tenure*ALOT	0.009	0.038	0.812
Tenure*ALOT^2	-0.000	0.002	0.800
Tenure*PLO	-1.076	0.124	0.000
Tenure*PLO^2	0.099	0.011	0.000
Tenure*PLOT	-0.198	0.033	0.000
Tenure*PLOT^2	0.029	0.005	0.000
Wald χ2		4,113.29	
N		48,820	
Log pseudolikelihood		0.022	

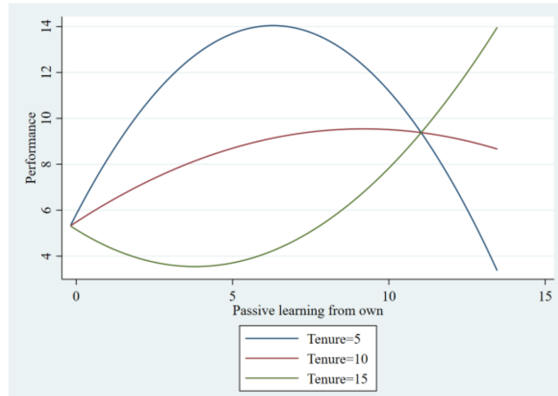
Discussion and Implications

Discussion

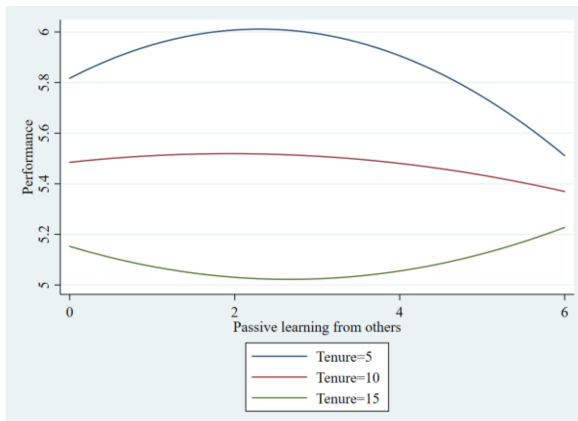
Our results support the previous hypothesis of a curved relationship, that is, active learning from own and active learning from others have a significant U-shaped relationship with performance, while passive learning from own and passive learning from others have a significant inverted U-shaped relationship with performance.



(a)



(b)



(c)

Figure 3. Moderating effect of Tenure

In order to facilitate the interpretation of the moderating effect in the nonlinear relationship, we use the image shown in Figure 3 to explain. Figure 3 (a) shows that with the growth of tenure, the learning curve of active learning from own gradually flattens, which indicates that the longer the individual studies, the weaker the effect of active learning from own. Since active learning from own is a kind of behavior that an individual takes the initiative to learn the knowledge he/ she is interested in, with the longer tenure and the deeper degree of active learning from own, the scope of individual learning is gradually narrowed and more limited to his/her personal interests, so the impact on his/her performance is gradually weakened. It shows that the longer the learning time is, the individuals need to consider changing their learning approach and focus.

Figures 3 (b) and 3 (c) show that the inverted U-shaped learning curves of passive learning from own and passive learning from others gradually flatten out as tenure increases, and change to a U-shaped learning curve when tenure increases further. This inversion of the shape of a curve from an inverted U shape to a U shape is called a "shape-flip"(Haans et al. 2016). As for the U-shaped flip phenomenon of passive learning, because passive learning is a learning approach that is subject to external pressure and lacks internal drive, the learning object and learning content of passive learning are usually not determined by the learner, that is to say, the content of individual learning is not necessarily what they are good at and interested in. Therefore, when tenure is small, that is, in the short-term learning, because passive learning can expand the learning scope of individuals to a certain extent, with the deepening of passive learning (including passive learning from own and passive learning from others), it has an inverted U-shaped impact on individual performance. When tenure is large, that is, in long-term learning, individuals have formed mature learning strategies and skills after a long period of learning. Therefore, when passive learning is relatively shallow, it may have an impact on individuals' original learning habits to a certain extent, resulting in a negative impact on individual performance. With the deepening of passive learning, the scope of individual learning is gradually broadened, and new learning strategies are formed, so it has a positive impact on individual performance.

Besides, hypothesis 3b is not supported by our results, which means the U-shaped relationship between active learning from others and performance will not evolute by the change of tenure. We speculate that the learning willingness of active learning from other is the highest among the four learning approaches so that the change of tenure has a little effect on the learning curve of active learning from others. Besides, we also think that with the increase of tenure, individuals are more likely to have path dependence on learning from own than learning from others, because individuals are more familiar to their own works, but in face with others' works, they still need to screen and understand them before deciding whether to learn from them, which is also the process of learning new things and breaks their original path dependence.

All in all, our results suggest that specific learning strategies can be adopted to promote the performance of individual works, depending on how long users have been learning: (1) Individuals with shorter learning time should take more active learning from own and adopt appropriate passive learning(including passive learning from own and passive learning from others). (2) Individuals with longer learning time should pay more attention to passive learning from own and passive learning from others, and reduce active learning from own.

Theoretical Implications

The findings of our study reveal some theoretical implications. Firstly, prior studies have produced inconsistent conclusions regarding the relationship between different learning approaches and performances. Furthermore, the research scenarios employed in such studies have always been offline, making it difficult to objectively classify the different learning approaches. Unfortunately, researches on individual learning behaviors based on objective data in online communities remain limited. Moreover, most of the previous measurement data on active and passive learning has come from questionnaires or experiments, which are often inadequate for further subdividing the various learning approaches. Secondly, based on the objective data from online communities, we further subdivide the individual learning approaches into active and passive learning from own and learning from others, rather than only from the two perspectives of active and passive learning or learning from own and learning from others. Through the detailed division of learning approaches, our study explains the reasons for the inconsistent conclusions of previous studies in more detail. Thirdly, we discuss the moderating effect of personal tenure on the learning curve, and further distinguish the changes and differences of the above learning approaches under different learning time spent. In light of the above discussion on the dynamics of learning, our results also shed some light on the inconsistency of previous studies. Most of the previous studies only focused on the learning situation at a certain time node for static research, but because the learning curve evolves dynamically with time, the conclusions based on the static perspective at different time points are not consistent. Our study and interpretation of the dynamic evolution of learning further reveals the dynamic changes in learning and fills the gap in previous studies that were only based on a static learning perspective.

Practical Implications

Our study also has some practical implications for users in online communities. In the process of learning and innovation, it should be noted that individuals should attach different degrees of importance to different learning approaches in different learning stages in order to achieve better performance. When the learning time is relatively short, individuals should pay more attention to strengthening their active learning from own process, and weaken their passive learning from own and learning from others. In other words, individuals should pay more attention to their personal learning preferences, and pay attention to and develop their personal interests early in their tenure. With longer learning time, individuals should pay more attention to passive learning from own and passive learning from others. In other words, individuals should pay more attention to external needs, enhance their ability to solve problems and learn works that other users are interested in later in their tenure, so as to create more popular works. Besides, for the open innovation community, it should pay attention to the evolution of different learning curves of users at different tenure of joining the platform, and then adopt appropriate strategies to promote users' learning and performance, so as to maintain the quality of the works and user activity, so that the platform can benefit from it.

Limitations and Future Research Directions

Considering the limitations, first of all, our results are based on data collected on only one open innovation community, NexusMods, and may not be applicable to other online communities. Therefore, more research needs to be done to test the validity of our findings in other communities. Secondly, although the measurement of learning approaches in this paper partly draws on some measurement methods in previous studies, there is no direct reference source because there is no previous study that classifies learning approaches as in this paper. It is also necessary to further find out whether there is a more appropriate measurement method in the follow-up research. Finally, the data in this paper are objective data from open innovation community, while most previous measurements of active learning and passive learning are in the form of questionnaires. Therefore, in the further studies, data from different channels can be combined to further verify the universality of the conclusion.

Conclusion

In modern times, organizations and individuals are increasingly aware that acquiring knowledge and using it effectively is the only way to gain a sustainable competitive advantage(Mahdi et al. 2019). The learning process is usually divided into several types of learning styles based on the offline scenario but have not reached a consistent conclusion. So we choose to focus on an online innovation community and make detailed division of individuals' diversified learning approaches. We further subdivide learning into four categories and study the dynamic evolution of learning curve, which further fills the gap in the research on individual learning curve in online communities. The results show that the four learning approaches have a curve impact on individual performance, and the tenure also has a moderating effect on the learning curve, and even the shape reversal phenomenon appears. This study makes not only theoretical contributions but also practical enlightenments. The results show that individuals should focus on different learning approaches at different stages of their learning, so as to improve the performance of their innovative works. Overall, our paper provides valuable guidance on learning behavior in online communities.

Acknowledgements

This work was supported in part by the National Social Science Foundation of China (22VRC153 and 18ZDA109).

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