Analysis of Effort and Tacit Knowledge Diffusion

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Abstract. The problems in tacit knowledge and its dissemination are introduced at the beginning, afterwards the influence of effort level on tacit knowledge dissemination is analyzed, and lastly the strategy selection and interaction mechanism between tutors and students under different effort levels is revealed. Furthermore, tutor supervision is selected as an influencing factor to establish an evolutionary game model between teachers and students. It is found that when individual students put in higher efforts, it not only enhances their own ability to absorb and transform tacit knowledge, but also promotes the optimization of the knowledge dissemination environment, strengthens the trust and willingness to cooperate between the two sides of the dissemination, and ultimately reaches an equilibrium state.

Keywords: Effort, Tacit Knowledge, Diffusion, Game Theory.

1 Introduction

Modern scholars consider knowledge management as a necessary and important part of the process of manifesting competitive advantage, and it is necessary to mention an important concept - tacit knowledge [1]. Peter Drucker [2] pointed out that tacit knowledge was very difficult to explain in words. It existed only in the human brain, mainly from continuous practice. So only in practice can one obtain tacit knowledge. Ikujiro Nonaka [3], a professor of knowledge management in Japan, believed that tacit knowledge involved different concepts, value guidelines and other factors of each person, and was a subjective kind of knowledge, which made it difficult to generalize all of the knowledge by applying unusual concepts.

As the driving force for innovative thinking, the dissemination of tacit knowledge is fatal for talent cultivation.[4] Tacit knowledge dissemination is constrained by many factors [5], which need to be considered and solved comprehensively from multiple

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perspectives, such as the knowledge itself, the disseminator and the receiver, the organizational environment and culture, the technological tools, and the social cognition and psychology [6]. Recipients' efforts play a crucial role in the effective dissemination of tacit knowledge [7], directly affecting their depth of understanding, absorption efficiency, knowledge transformation, and ability to share and innovate knowledge. Adopting SIR model, Liang Qianqian [8] explores the mechanism of tacit knowledge dissemination in Newman-Watts small-world networks, replacing the diffusion term with the adjacency matrix of network to achieve dissemination, and thus effectively accelerating tacit knowledge dissemination. Weixu Ding's [9] findings show that individuals can learn tacit knowledge via imitating, adapting to the current situation, and then creating new ideas to solve problems. His research proves that adaptive learning has a mediational role in the relationship between imitation and creation. Therefore, in the process of tacit knowledge dissemination, full attention should be paid to the recipients' efforts, and their learning motivation should be stimulated through the provision of learning resources and support [10], the establishment of a feedback mechanism, the creation of a positive learning atmosphere and other strategies, so as to improve the effect and quality of tacit knowledge dissemination.

2 Analysis of the Current Status of Student Learning

The recipients' efforts will affect the effect of tacit knowledge dissemination, the degree of mastery of tacit knowledge, and even the learning performance, which in turn relates to the quality of talent cultivation.

(1) Analyze from the perspective of learning input. In 2015, Zepke proposed that learning input meant students could actively use their own learning experience to think and summarize in the process of learning. In 2017, Balwant held that learning input was the input of students' active psychology and behavior in learning activities. In China, the concept of learning input initially originated from input at work [11], and Su Hong believed that learning input contained material input, time input and spiritual input. Sun Weiwen [12] believed that learning input could be divided into three parts, the first part behavior, the second part cognition, and the third part emotion, which could be specifically extended according to the specific situation.

(2) Analyze from the perspective of learning autonomy. In recent years, there has been a heated discussion in the Western educational community about whether or not to take autonomy as the purpose of education [13]. Cuppers S.E. advocates that the focus on "caring for the self" should be regarded as one of the foundational purposes of education, while Haji I. et al. believe that the formative purpose of autonomy, together with the fulfillment of desires, constitutes happiness, and therefore education should include autonomy. An experiment on autonomy in China found that learning with autonomy is very helpful in enhancing students' intelligence and performance [14]. Some scholars found a significant positive correlation between the exercise of learning autonomy and their academic performance [15]. Junying Chai advocates that teachers should be responsible for developing learning autonomy, and that the teaching method of excessive lecturing should be changed to decentralize learning.

(3) From the perspective of learning gains. Schaufeli pointed out that the higher the level of students' commitment to learning, the higher their academic performance; the higher the level of laxity, the lower their academic performance. In 2009, Gayles found that the teachers' teaching behaviors and attitudes had a certain impact on students' learning gains; Kuh pointed out that increasing the level of interaction between teachers and students could effectively promote and enhance the learning of students. In 2012, Tan Ying conducted a survey and used Logistic regression to analyze the degree of influence of students' family background on learning gains.

3 Evolutionary Analysis of Student Effort

3.1 Factors Influencing Student Effort

The factors affecting the level of effort of the student group within the mentoring system are complex and varied, including various aspects such as exogenous and endogenous factors, which may act individually or jointly, and the analysis of these factors is necessary to study the evolution of the students' behavior. Some of the influencing factors of students' effort level are:

(1) Supervision by mentors. Supervision by the tutor is a key factor influencing the learning behavior of the student group, and the tutor's ability, responsibility, and supervision determine the students' learning interest and learning effect, which in turn will affect the students' effort to learn tacit knowledge.

(2) Learning Motivation. Learning motivation is the internal power that directly promotes and maintains students' learning of tacit knowledge, including learning needs, learning expectations, learning interests, learning attitudes, etc., in which learning needs and learning interests are the internal driving force of students, learning expectations are the triggers of students' learning behaviors, and learning attitudes are the important factors to ensure that students' learning persistence.

(3) Learning feedback. Refers to the corresponding information that students will learn the harvest passed on to students, will affect the students' subsequent learning status, positive feedback and negative feedback have different roles, positive and negative feedback will determine to a certain extent whether the students' subsequent efforts will make the students' subsequent efforts to adjust the degree of effort.

(4) Peer pressure. Refers to the pressure of the student group on each other, when there is competition between students, there will be corresponding pressure within the student group, this peer pressure usually increases the level of effort of students.

(5) Parental pressure. Parents as the student's guide, its attitude, requirements and behavior will subconsciously affect the student's effort.

(6) Institutional constraints. The constraints, institutional requirements, and incentive system of the mentor team will create a different learning atmosphere and constrain the student's behavior, which in turn affects the level of student effort.

3.2 Evolutionary Analysis of Student Effort

In the game between students and tutors, both sides are limited rationality. They both have the ability to imitate as well as learning. Tutors' supervision will affect the students' decision-making, and then produce mutation, meanwhile, the student group's effort behavior will be fed back, aiding the tutor to make strategic choices. They constantly trial, make error and adjustment, to get the maximum benefit, and eventually reach an equilibrium. Thus, the evolutionary game model is established.

When studying students' efforts, an asymmetric replication dynamic model is established based on the game between tutors and students, and hypotheses are put forward based on the constructed model:

(1) The tutor and the student are both participants in a finite rational game;

(2) The student can choose effortful learning strategy A and non-effortful learning strategy B, which are abbreviated as (A, B) The tutor can adopt two strategies of supervising C and non-supervising D, which are abbreviated as (C, D);

(3) Let the benefit of students' efforts be a (including the improvement of grades, self-satisfaction, etc.); b denotes the teacher's recognition and praise; c is the time and energy cost of efforts; d denotes the benefit of students' non-efforts (including the additional rest and recreation time, and the reduction of energy input, etc.); and e denotes the criticisms and penalties of students' supervision by the tutor.

(4) Let the benefit of supervision by the tutor be f (the satisfaction and sense of achievement that the tutor gets from the feedback of the student's effort); g is the cost of time and energy that the tutor pays for supervising the student; h represents the benefit of the tutor's non-supervision (including the windfall of the student's effort, and the sense of fluke); and i represents the decline in the tutor's reputation and word-of-mouth due to the student's slacking off, and the punishment of the school's performance appraisal. Note: Since whether or not the tutor strictly supervises does not affect the tutor's salary w, the salary is not counted.

(5) Let the proportion of students adopting strategy A be x, then the proportion of students choosing strategy B be $1-x$. Let the proportion of tutors choosing strategy C be y, then the proportion of tutors choosing strategy D be $1-y$, where $x, y \in (0, 1)$.

(6) Let U_A and U_B denote the expected returns when students choose strategies A and B, respectively; U_C and U_D denote the expected returns when mentors choose strategies C and D, respectively; and $\overline{U}_1$ and $\overline{U}_2$ denote the average returns for the student and mentor groups, respectively.

The six assumptions are synthesized to build the payment matrix of the student-mentor game (as shown in Table 1).

Table 1. payment matrix of the student-mentor game

		mentor	
		monitor C	non-monitor D
Student	Effort A	$a+b-c, f-g$	$a-c, h$
	Effortless B	$d-e$, $-g-i$	d, $-i$

Based on the given assumptions and the game matrix the expected return as well as the average return for the student population can be obtained:

$$U_A = y(a + b - c) + (1 - y)(a - c) = a - c + by \quad (1)$$

$$U_B = y(d - e) + (1 - y)d = d - ey \quad (2)$$

$$\overline{U}_1 = xU_A + (1 - x)U_B = x(a - c + by) + (1 - x)(d - ey) \quad (3)$$

Similarly one can find the expected return as well as the average return for the group of mentors:

$$U_C = x(f - g) + (1 - x)(-g - i) = -g - i + (f + i)x \quad (4)$$

$$U_D = xh + (1 - x)(-i) = -i + (h + i)x \quad (5)$$

$$\overline{U}_2 = yU_C + (1 - y)U_D = y[-g - i + (f + i)x] + (1 - y)[-i + (h + i)x] \quad (6)$$

According to the theory of replicator dynamics, a strategy will be continued if its return is higher than the average return of the group, and the replicator dynamics equation is a dynamic differential equation that describes the frequency with which a strategy is selected. According to the Malthusian dynamic equation, the growth rate of students' selection of strategy A is equal to the difference between its return and the average return, and t is used to represent time, so the replicator dynamic equation of the student population is:

$$f(x, y) = \frac{dx}{dt} = x(U_A - \overline{U}_1) = x(1 - x)[a - c - d + (b + e)y] \quad (7)$$

Similarly the equation for the replication dynamics of the mentor population can be derived as:

$$g(x, y) = \frac{dy}{dt} = y(U_C - \overline{U}_2) = y(1 - y)[-g + (f - h)x] \quad (8)$$

3.3 Stability Analysis of Evolutionary Game Models

The evolutionary equilibrium point can be derived from the replicated dynamic equations for the student and mentor populations.

Let Eq.(7) $f(x, y) = 0$, obtain the solution: $x^* = 0$, $x^* = 1$, $y^* = \frac{c+d-a}{b+e}$.

Let Eq.(8) $g(x, y) = 0$, obtain the solution: $y^* = 0$, $y^* = 1$, $y^* = \frac{g}{f-h}$.

Five equilibrium points are obtained, which are: O(0, 0), P(0, 1), Q(1, 0), M(1, 1), N$(\frac{g}{f-h}, \frac{c+d-a}{b+e})$.

According to evolutionarily stable strategy (ESS), a stable state must be resistant to mutating factors. Assuming that the equilibrium point of the evolutionary stabilization strategy is x_0, when there is a disturbance that makes x higher than x_0, then $f(x) = \frac{dx}{dt}$ must be less than 0, that is $f'(x_0) < 0$; when there is a disturbance that makes x lower than x_0, then $f(x) = \frac{dx}{dt}$ must be greater than 0, that is $f'(x_0) > 0$.

The stability of the evolutionary equilibrium point can be derived from the local stability analysis of the Jacobi matrix, which is constructed according to the replicated dynamic equations J as:

$$J = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \begin{bmatrix} \frac{\partial f(x,y)}{\partial x} & \frac{\partial f(x,y)}{\partial y} \\ \frac{\partial g(x,y)}{\partial x} & \frac{\partial g(x,y)}{\partial y} \end{bmatrix}$$
$$= \begin{bmatrix} (1-2x)[a-c-d+(b+e)y] & x(1-x)(b+e) \\ y(1-y)(f-h) & (1-2y)[-g+(f-h)x] \end{bmatrix}$$

If the equilibrium point sought makes the Jacobi matrix satisfy:

(1) Matrix traces, $\mathrm{tr}J = a_{11} + a_{12} < 0$,

(2) determinant, $\det J = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = a_{11}a_{22} - a_{12}a_{21} > 0$

The equilibrium can be shown to be evolutionarily stable strategy.

Based on common sense set $f < h$, $a_1 = c + d - b - e$, $a_2 = c + d$, $h_1 = f - g$, then it is analyzed in six specific cases:

Case 1: When $0 < a < a_1$ and $h < h_1$, the evolutionarily stable strategy is (B, D), the local stability analysis is shown in Table 2.

Table 2. Local stability of the equilibrium point in Case 1

Equilibrium Point	det$J$	tr$J$	Result
O(0, 0)	+	-	ESS
P(0, 1)	-		saddle point
Q(1, 0)	+	+	point of instability
M(1, 1)	-		saddle point

Case 2: When $0 < a < a_1$ and $h > h_1$, the evolutionarily stable strategy is (B, D), the local stability analysis is shown in Table 3.

Table 3. Local stability of the equilibrium point in Case 2

Equilibrium Point	det$J$	tr$J$	Result
O(0, 0)	+	-	ESS
P(0, 1)	-		saddle point
Q(1, 0)	-		saddle point
M(1, 1)	+	+	point of instability

Case 3: When $a_1 < a < a_2$ and $h > h_1$, the evolutionarily stable strategy is (B, D), the local stability analysis is shown in Table 4.

Table 4. Local stability of the equilibrium point in Case 3

Equilibrium Point	det$J$	tr$J$	Result
O(0, 0)	+	-	ESS
P(0, 1)	+	+	point of instability
Q(1, 0)	-		saddle point
M(1, 1)	-		saddle point

Case 4: When $a > a_2$ and $h < h_1$, the evolutionary stable strategy is (A, C), the local stability analysis is shown in Table 5.

Case 5: When $a > a_2$ and $h > h_1$, the evolutionary stable strategy is (A, D), the local stability analysis is shown in Table 6.

Case 6: When $a_1 < a < a_2$ and $h < h_1$, the evolutionarily stable strategies are (B, D) and (A, C), the local stability analysis is shown in Table 7.

Table 5. Local stability of the equilibrium point in Case 4

Equilibrium Point	det*J*	tr*J*	Result
O(0, 0)	-		saddle point
P(0, 1)	+	+	point of instability
Q(1, 0)	-		saddle point
M(1, 1)	+	-	ESS

Table 6. Local stability of the equilibrium point in Case 5

Equilibrium Point	det*J*	tr*J*	Result
O(0, 0)	-		saddle point
P(0, 1)	+	+	point of instability
Q(1, 0)	+	-	ESS
M(1, 1)	-		saddle point

Table 7. Local stability of the equilibrium point in Case 6

Equilibrium Point	det*J*	tr*J*	Result
O(0, 0)	+	-	ESS
P(0, 1)	+	+	point of instability
Q(1, 0)	+	+	point of instability
M(1, 1)	+	-	ESS
$N(\frac{g}{f-h}, \frac{c+d-a}{b+e})$	-		saddle point

3.4 Data Simulation Analysis

To further visualize and analyze the evolutionary game paths of the student and the tutor under the conditions of finite rationality, as well as the influence of the changes of each parameter of the inputs and benefits of the strategy on the final evolutionary results, MATLAB is used to simulate and analyze the evolutionary process of the two sides of the game under the above six conditions.

The simulation using a two-dimensional evolutionary game model can accurately portray the game process in which the participants interact with each other. Using the cyclic algorithm, the initial state is selected as (0.1, 0.1), the step size is 0.1, and the final state is (0.9, 0.9), where the horizontal coordinate indicates the number of cycles of the system evolution, and the vertical coordinate indicates the probability of the two sides of the game adopting the strategy. The simulation results are:

Case 1: When $0 < a < a_1$ and $h < h_1$, ESS is (B, D), values are assigned to each parameter in the gain matrix as: $a = 0.08$, $b = 0.5$, $c = 0.6$, $d = 0.3$, $e = 0.3$, $f = 0.7$, $g = 0.5$, $h = 0.1$. The simulation results are shown in Fig. 1(1).

As can be seen in Fig. 1(1), the final stable state of the evolutionary game is the point (0, 0), regardless of the values of the initial states of the two sides of the game. Therefore, in that case, the student tends to adopt a no-effort strategy, while the tutor tends to adopt a no-supervision strategy.

Case 2: When $0 < a < a_1$ and $h > h_1$, evolutionary stabilization strategy is (B, D), values are assigned to each parameter in the gain matrix as: $a = 0.08$, $b = 0.5$, $c = 0.6$, $d = 0.3$, $e = 0.3$, $f = 0.7$, $g = 0.5$, $h = 0.3$. The simulation results are shown in Fig. 1(2).

As can be seen in Fig. 1(2), the final stable state of the evolutionary game is the point (0, 0), regardless of the value of the initial state of the two sides of the game. Therefore, in that case, the student tends to adopt a no-effort strategy, while the tutor tends to adopt a no-supervision strategy.

Case 3: When $a_1 < a < a_2$ and $h > h_1$, evolutionary stabilization strategy is (B, D), assign values to each parameter in the gain matrix as: $a = 0.8$, $b = 0.5$, $c = 0.6$, $d = 0.3$, $e = 0.3$, $f = 0.7$, $g = 0.5$, $h = 0.3$. The data simulation results are shown in Fig. 11(3).

As can be seen in Fig. 1(3), the final stable state of the evolutionary game is the point (0, 0), regardless of the value of the initial state of the two sides of the game. Thus, in that case, the student tends to adopt the no-effort strategy, while the tutor tends to adopt the no-supervision strategy. That is, when the gains in terms of improved grades and self-satisfaction from student effort, such as a, are smaller than the relative gains from effort relative to effort versus no effort, or when the gains from student effort, such as a, are less than the sum of the gains from effort relative to effort versus no effort and greater than the sum of the relative gains from effort relative to effort versus no effort, and the gains from mentor non-supervision are greater than the net gains from supervision, the student tends to choose the no-effort strategy, and the mentor tends to choose the no-supervision strategy.

Case 4: When $a > a_2$ and $h < h_1$, evolutionary stable strategy is (A, C), values are assigned to each parameter in the gain matrix as follows: $a = 1.2$, $b = 0.5$, $c = 0.6$, $d = 0.3$, $e = 0.3$, $f = 0.7$, $g = 0.5$, $h = 0.1$. The results of the data simulation are shown in Fig. 1(4).

As can be seen in Fig. 1(4), the final stable state of the evolutionary game is the (1, 1) point, regardless of the values taken by the initial states of the two parties to the game. That is, when the student's gain from effort, a, is greater than the sum of the payoffs from effort and no effort, and the mentor's gain from not supervising is less than the net gain from supervising, the student tends to choose the effort strategy and the mentor tends to choose the supervision strategy.

Case 5: When $a > a_2$ and $h > h_1$, the evolutionary stable strategy is (A, D), assign values to each parameter in the gain matrix as follows: $a = 1.2$, $b = 0.5$, $c = 0.6$, $d = 0.3$, $e = 0.3$, $f = 0.7$, $g = 0.5$, $h = 0.3$. The results of the data simulation are shown in Fig. 1(5).

As can be seen in Fig. 1(5), the final stable state of the evolutionary game is the point (0, 1), regardless of the values taken by the initial states of the two parties to the game. When the gain a from the student's effort is greater than the sum of the gains from effort and no effort, and the gain from the mentor's non-supervision is greater than the net gain from supervision, the student tends to choose the effort strategy and the mentor tends to choose the non-supervision strategy.

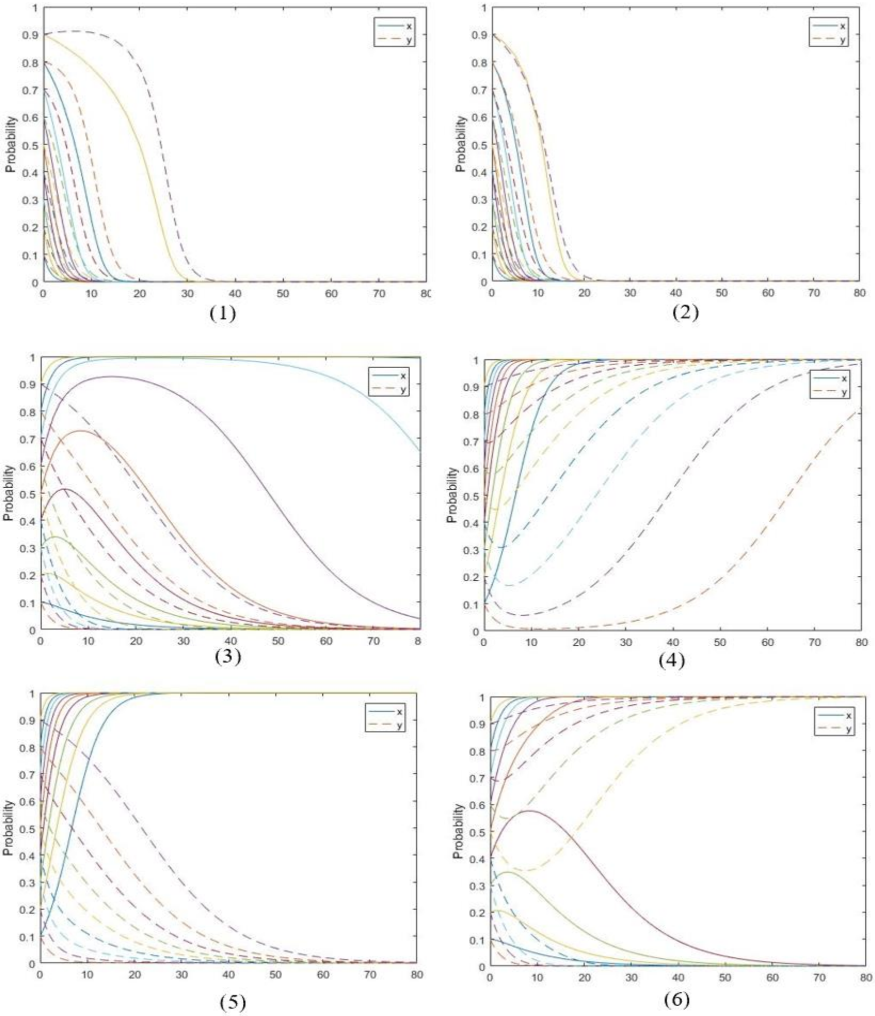

Fig. 1. Results of the data simulation

Case 6: When $a_1 < a < a_2$ and $h < h_1$, the evolutionarily stable strategies are (B, D) and (A, C), assign values to each parameter in the gain matrix as follows: $a = 0.8$, $b = 0.5$, $c = 0.6$, $d = 0.3$, $e = 0.3$, $f = 0.7$, $g = 0.5$, $h = 0.1$. The results of the data simulation are shown in Fig. 1(6).

As can be seen in Fig. 1(6), when $0 < x < 0.5$ and $0 < y < 0.5$, the final stable state of the evolutionary game is the point (0, 0), when the student tends to adopt the no-effort strategy and the tutor tends to adopt the no-supervision strategy. When $0.5 < x < 1$ and

$0.5 < y < 1$, the final stable state of the evolutionary game is the point (1, 1), at which time the student tends to adopt the strategy of effort and the mentor tends to adopt the strategy of supervision.

4 Research Analysis and Recommendations

According to the analysis of the evolutionary results, it is concluded that the game process of the student and tutor groups will eventually reach four different evolutionary equilibrium states depending on the benefits and expenditures, and the changes in benefits and expenditures will cause changes in strategy choices. From the perspective of a third party, the situation in which tutors supervise students and students study hard is the optimal state, i.e., the evolutionary stability strategy is expressed as (A, C).

A comprehensive analysis of the student population in combination with evolutionary stability shows that when $a > c + d$ and $h < f - g$, students and tutors tend to choose the evolutionarily stable strategy, i.e., when the gains from students' effort such as improved grades and self-fulfillment are greater than the sum of time and effort expended and the additional gains from not exerting effort and the windfall gained from tutors' non-supervision is less than the net gain from supervision, the students' choice of the evolutionary equilibrium will be formed when the student chooses the "effort" strategy and the tutor chooses the "supervision" strategy. Based on this optimal goal, the two perspectives of students and tutors are combined with the evolutionary stability analysis to give the following recommendations: (1) From the perspective of the student population, to realize the state of students effortful learning, the benefits of students' effortful behaviors should be greater than the expenditures, and the expenditures of non-effortful behaviors should be greater than the benefits. To increase students' performance improvement, self-satisfaction, and tutor's recognition and reward, it is necessary to reduce the time and energy invested in studying, increase tutor's criticism and punishment, and reduces entertainment. (2) From the tutor's point of view, to realize the state of strict supervision by the tutor, it is essential to make the benefit of supervision by the tutor greater than the expenditure, and make the expenditure of non-supervision greater than the benefit. That is, it is necessary to increase the students to give positive feedback, increase the sense of satisfaction, reduce the time and energy investment in supervision, and the school to increase the punishment to put an end to the tutor's slackness and fluke mentality.

5 Conclusions

The high degree of students' efforts plays a contributing role in the dissemination of tacit knowledge, and hence students' ability to possess tacit knowledge will be enhanced. In real life, the degree of students' mastery of tacit knowledge is also related to other factors, such as the higher the individual's learning ability, the more conducive to the mastery of tacit knowledge. In addition to the emergence of new technologies, more and more people can utilize high technology to assist themselves in mastering tacit knowledge. In the future, the level of science and technology will also be an influential factor to be considered in the study of tacit knowledge dissemination.

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