Exploration of Learning Types and Innovation Performance : Dynamic Process-Phase Approach

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ABSTRACT The exploration of learning types and innovation performance based on the trade-off and interaction between exploitative and exploratory learning is adopted in this study. LPM (Learning Progress Motivation) algorithm converts the interaction of exploitative and exploratory learning of 183 engineers into the process-phase quantitative data through the innovation process. Three learning types are classified. The influence of each learning type on innovation performance is inquired at a process-phase base.

Key words : Learning, innovation performance, process-phase.

Introduction

1. Learning versus Innovation

Both exploitative and exploratory learning govern innovation (March, 1991). Although achieving a proper balance between exploratory and exploitative learning is not an easy task (He & Wong, 2004; Katila & Ahuja, 2002). A negative interaction between exploratory and exploitative learning resonates with research that notes appropriate balance of exploratory and exploitative learning needs a high — low combination rather than a high — high combination (Li, Chu, & Lin., 2010).

2. Process-Phase Time-Frame Based Exploration

The past researches of learners' characteristic in utilizing exploitative and exploratory learning have not been conducted in a process-phase time-frame based exploration (Benner & Tushman, 2003; Cao, Gedajlovic, & Zhang, 2009; Crossan, Vera, & Nanjad, 2008; Dunlap et al, 2014; Gibson & Birkinshaw, 2004; Gilbert, 2005; Gupta, Smith, & Shalley, 2006; He & Wong, 2004; Katila and Ahuja, 2002; Kostopoulos & Bozionelos, 2011; Li, Chu, & Lin, 2010;

Lubatkin, Simsek, Ling, & Veiga, 2006; Nerkar, 2003; Voss, Sirdeshmukh, & Voss, 2008) until the study of Chuang, Chang, and Hsu (2012). By using a process-phase time-frame based quantitative converter—LPM (Learning Progress Motivation) algorithm, the interaction of exploitative and exploratory learning of individuals is able to be converted into a process-phase quantitative data through the entire innovation process.

3. Learning Types versus LPM Characteristic Curves

In this study, LPM algorithm is adopted in a situated experiment of anticipation games which simulates innovation processes. The process-phase time-frame based learning records of subjects, which are generated in experiments, are converted into quantitative data by LPM algorithm. A graphic curve, named LPM curve, is generated by LPM algorithm for each subject in the experiment process. Then the LPM characteristic curve is generated by conducting multifactor linear regression on the LPM curves of specified group. In the other word, the LPM characteristic curve represents the overall learning characteristic of the specified subjects. In the study of Hsu and Chang (2015), the LPM characteristic curves are classified as Learning Type A, Learning Type B, and Learning Type C according to the unique evolutionary interaction relationship between exploitative and exploratory learning in the innovation process.

In this study, authors explore the innovation performance of individual learning types by using the LPM algorithm through the entire innovation process.

Method

1. Situated experiments

The concept of the situated experiment applied in this study is similar to the one applied in the study of Chuang, Chang, and Hsu (2012). Subjects anticipate unknown target numbers by the strategy of maximizing their learning progress.

2. Subjects

183 R&D engineers from 45 firms in Taiwan are selected randomly as the subjects of the experiment in this study.

3. Mechanisms of Experiments

Subjects are requested to anticipate target numbers from number 1 to 200. The mechanism of anticipation is shown below:

- **Generation of target zone**: Three target numbers of the target zone are generated by the computer randomly in terms of *T*, *T*-1, and *T*+1.
- **Strategies of anticipation**: The strategy $M_{exploratory}$ is defined as the individual subject picks the number generated by the computer randomly, which simulates exploratory learning. The strategy $M_{exploitative}$ is defined as the individual subject induces the numbers based on evaluating learning progress,

which simulates exploitative learning.

- **Evaluation of learning progress**: The values of learning progress and cumulative learning progress are calculated according to LPM algorithm for the evaluation at each anticipation step.
- **Decision making of the anticipation**: An individual subject adopts either $M_{exploitative}$ or $M_{exploratory}$ to predict a number corresponding to the learning progress and the cumulative learning progress.

Tool

1. LPM Algorithm

LPM algorithm evaluates the learning progress by calculating the decrease of learning errors between two continuous learning steps (Chuang, Chang, and Hsu, 2012).

In the innovation process, a subject predicts an output signal *O(n)* corresponding to the anticipations at step n. The LPM reward received at step n is *R(n)*. The goal of the subject is to maximize the amount of rewards received in a given step frame.

Subjects tend to receive maximal cumulative LPM reward or equivalent maximal learning progress through the innovation process. At specific step n, the value of error *e(n)*, which is the difference between the predicted *O(n)* and the target number *T*, is calculated as equation (1).

$$e(n) = |O(n) - T| \tag{1}$$

The learning progress *p(n)* is defined as the decrease of errors between two continuous anticipations . In case of an increasing *e(n)*, learning progress is zero. Since *R(n)* equals to *p(n)*. Corresponding equations are represented as equation (2) and (3):

$$R(n) = p(n) = e(n-1) - e(n) \ : \ e(n) < e(n-1) \tag{2}$$

$$R(n) = p(n) = 0 \ : \ e(n) \geqq e(n-1) \tag{3}$$

Refer to equation (4), in each step, the cumulative learning progress *P(n)* is computed as the integration over time of previous *p(n)* or *R(n)*.

$$P(n) = \Sigma^{n}_{j=1}\, p(n) = \Sigma^{n}_{j=1}\, R(n) \tag{4}$$

In order to evaluate the learning progress performed through exploitative learning ($M_{exploitative}$) and exploratory learning ($M_{exploratory}$) simultaneously in the entire innovation process, the cumulative exploitative learning progress $P_{exploitative}(n)$ and the cumulative exploratory learning progress $P_{exploratory}(n)$ obtained for a specific subject at step n are compared simultaneously to come out the comparative learning progress ratio *RP(n).*

$$RP(n) = P_{exploitative}(n) \,/\, P_{exploratory}(n)$$
$$= \Sigma^{n}_{j=1} R_{exploitative}(n) \,/ \Sigma^{n}_{j=1} R_{exploratory}(n) = RR(n) \quad (5)$$

2. Innovation Performance

The innovation efficiency is taken as the indicator of innovation performance. The innovation efficiency $E_{innovation}$ is defined as the ratio of the period of steady-state condition to the period of a specific corresponding LPM cycle. The period is represented as the steps retained in the steady-state condition or a specific LPM cycle. It is shown as equation (6):

$$E_{innovation} = P_S \,/\, P_{LPM} \quad (6)$$

where

$E_{innovation}$ = innovation efficiency

P_S = the steps retained in the steady-state condition

P_{LPM} = the steps retained in a specific LPM cycle

Results

1. Learning Characteristics versus Learning Types

183 individual LPM curves are classified into three LPM characteristic curves based on the similarity of curve modal, which refers to Learning Type A, B, and C accordingly. Refer to Table 1, 56 subjects (30.6%) are classified as Learning Type A, 54 subjects (29.5%) as Learning Type B, and 73 subjects (39.9%) as Learning Type C.

Table 1. Distribution chart of learning types

Learning Type A		Learning Type B		Learning Type C		Total	
56	30.6%	54	29.5%	73	39.9%	183	100%

Learning Type A represents the characteristic of exploitative learning preferred. Learning Type B represents the characteristic of exploratory learning preferred. Learning Type C represents the characteristic of blended exploitative and exploratory learning.

2. Learning Types versus Innovation Performance

Refer to Fig. 1, the innovation performance of individual Learning Type is calculated according to equation (6) through the entire innovation process.

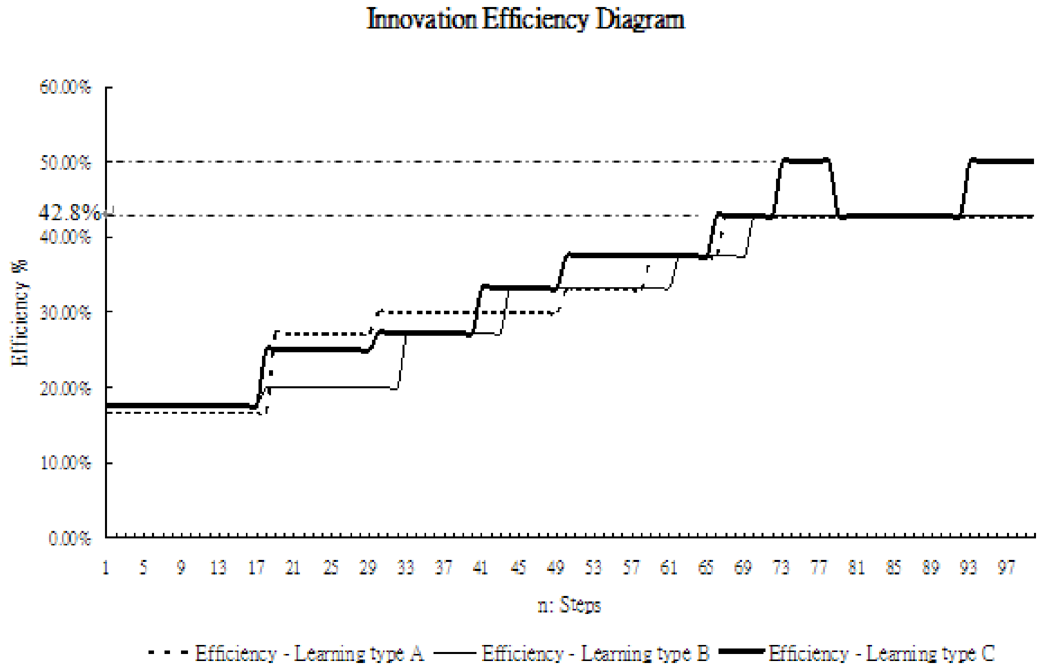

Fig. 1. Innovation performance – Learning Type A, B, and C

Discussion and Conclusion

1. Innovation Performance

Refer to Fig. 1, the subjects of Learning Type C achieve the highest innovation performance. By comparing the subjects' performance of Learning Type A and B, The subjects of Learning Type B achieve better innovation performance from the 1st step to the 17th step. And the subjects of Learning Type A achieve better innovation performance from the 18th step to the 40th step. Therefore, effective balancing of exploratory and exploitative learning in different innovation phases requires a high-low combination rather than a high-high combination.

2. Sustainable Innovation

Both the subjects of Learning Type A and B achieve similar innovation performance after the 49th step. Different from the subjects' performance of learning type A and B, the subjects of Learning Type C approach 50% efficiency twice after reaching 42.8% efficiency, which represents sustainable innovation. On the other hand, both the subjects of Learning Type A and B stay at 42.8% efficiency till the end of innovation process. Such findings is in line with the study of Kim et al. (Kim, Song, & Nerkar, 2012) that key to the innovation strategy is to strike the right balance between exploitative and exploratory learning.

The subjects with the characteristic of blended exploitative and exploratory learning (Learning Type C) achieve the best innovation performance with sustainable innovation. Hence, sustainable innovation established by the well balance between exploitative and exploratory learning drives the subjects of Learning Type C to achieve the best innovation performance compared with the subjects of Learning Type A and B.

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A successful man is one who can lay a firm foundation with the bricks others have thrown at him.

~ David Brinkley