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Dynamically Explore the Characteristic of Individual Learning Type in Innovation Process

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Abstract – **The longitudinal relationship between exploitative & exploratory learning and innovation performance has not been researched dynamically and quantitatively by the time-domain frame in the innovation process. The dynamic exploration of the characteristic of individual learning type by exploring time-frame based quantitative data on the trade-off and interaction between exploitative and exploratory learning for different individual learning types are adopted in this study. LPM (Learning Progress Motivation)algorithm converts the interaction of exploitative and exploratory learning of 154 R&D engineers into the process-phase quantitative data through the innovation process. Three learning types are classified by the unique complementarity characteristic between exploitative and exploratory learning.**

Keywords – **Learning Type, Innovation, Process-Phase, Time-Frame.**

I. Introduction

A. Learning versus Innovation

Both exploitative and exploratory learning govern innovation [1]. Most organizational learning researchers agree that there is a need for both exploratory and exploitative learning[1]-[5]. Although achieving a proper balance between exploratory and exploitative learning is not an easy task, existing theory suggests that a failure to do so will likely lead to a decline in organizational performance [1], [4]-[8].

Appropriate balance of exploratory and exploitative learning needs a high — low combination rather than a high — high combination [9]. It implies that exploratory learning (exploitative learning) could be more valuable to new product development when it is coordinated with a rationale level of exploitative learning (exploratory learning).

B. Process-Phase Time-Frame Based Exploration

The ambidexterity is viewed as a proactive learning process in which firms can purposefully seek and exploit new and existing resources that can lead to the discovery and creation of both exploratory (breakthrough) and exploitative (incremental) types of technological innovations [10]. The current understanding of the distinctiveness of exploratory and exploitative learning in differential innovation phases of the new product development process is still unclear.

In general, the past researches of learners' characteristic in utilizing exploitative and exploratory learning have not been conducted in a process-phase time-frame based exploration[2],[4], [6]-[30] because of no available effective technology.

Therefore, a process-phase time-frame based quantitative converter is required for such research on the time-frame longitudinal exploration between exploitative learning and exploratory learning. With the process-phase time-frame based technology－LPM algorithm [31], the time-frame based LPM characteristic curve, a visual-aided tool, is generated through the innovation process by converting the interaction of exploitative and exploratory learning of individuals into a process-phase quantitative data.

C. Exploration of Learning Types

Based on the LPM algorithm [31], the authors explore the learning type through the further study on the process-phase time-frame based LPM curves which are generated individually by the subjects in the innovation process. In this study, LPM curves generated by the subjects are classified into several specific groups in which are classified by the unique complementarity characteristic between exploitative and exploratory learning. The unique complementarity characteristic is represented as the similarity of the curve modal, which is identified through the specific group of LPM curves. Then the specific group of LPM curves, classified as the specific group, are converted into a LPM characteristic curve accordingly.

Therefore, the specific curve modal of the LPM characteristic curve is classified as a specific learning type accordingly which represents the unique evolutionary interaction relationship between exploitative and exploratory learning.

Furthermore, LPM characteristic curve generated by LPM algorithm is proved in this study to be a process-phase time-frame based user-friendly tool for visually diagnosing the influence caused by the interaction of exploitative and exploratory learning between individual learning types in the innovation process. In summary, the core value of this study is to:

1) Interpret dynamic interaction relationship of exploitative learning and exploratory learning through the innovation process by a process-phase time-frame based user-friendly visualized tool-LMP characteristic curve.

2) Explore subjects' characteristic of individual learning type through the interaction relationship of exploitative and exploratory learning at a process-phase time-frame base.

II. Theory

A. Learning and Innovation

The complex demands of today's innovation contexts indicate the need of integrating exploratory and exploitative learning [6], [15], [22]-[24], [32] to simultaneously pursue both exploitative and exploratory innovations [9]-[12], [14], [20]-[21], [30]. Sustainable innovation performance in organizations is rooted in exploiting existing competences and exploring new opportunities [6],[16], that is, to explore new capabilities while exploiting existing ones [7],[26]-[27].

B. Maximal Learning Progress (MLP) Reward

Kaplan and Oudeyer [33]present an intrinsic reward system that drive an agent to progress in learning given its embodiment and environment in which it is placed. It pushes an agent pursue situations in which it maximizes its learning progress. Kaplan and Oudeyer [33]define it as MLP reward.

The learning target is not fixed but changeable according to actual contexts in innovation processes. At a specific learning step, the difference between the learning achievement and learning target is named learning error. And the difference of learning errors between two continuous learning steps is defined as learning progress. The learning progress is the reward received by the learner. The learning progress (reward) becomes 0 while the difference of learning errors is negative, that is, there is no learning progress when the learning error increases.

C. Learning Progress Motivation (LPM)

LPM, noted in the study of Chuang, Chang, and Hsu [31], which is based on the concept of MLP reward, is designed to motivate people to adapt both exploratory and exploitative learning according to innovation contexts in order to lead people into effective exploratory and exploitative innovation.

The basic difference of the reward mechanism between MLP reward and LPM is that LPM evaluates both exploratory and exploitative learning but MLP reward treats learning as a single factor. In this study, LPM is adopted in a situated experiment of anticipation games which simulates innovation processes without an explicit and fixed target to achieve. 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 at process-phase time-frame base in the experiment process. The LPM curve is used for further analysis to explore subjects' learning types and the corresponding innovation situation.

D. Contextual Ambidexterity

Gibson and Birkinshaw [16]propose that contextual ambidexterity, whereby organizations encourage individuals to make their own choices as to how they divide their time between exploratory and exploitative learning, is a viable way of ambidexterity. An ambidextrous firm can be capable of operating exploratory and exploitative learning simultaneously and such a firm can achieve innovation performance superior to those emphasizing one approach [34]. Exploitative and exploitative learning activities are complementary in the product innovation process because exploitative learning can transfer the advantages or outcomes (innovativeness) of exploratory learning into product innovation performance, thus supporting the mutually complementary perspective [18]. On the other hand, the findings extend the dynamic view of ambidexterity [35]-[36] into new product development process where managing the two learning activities should temporarily cycle through periods of exploitation and exploration.

III. METHODS

A. Situated Experiments

The authors design an experiment to record subjects' learning records during innovation processes. The concept of the situated experiment applied in this study is similar to the one applied in the study of Chuang, Chang, and Hsu [31]. Subjects anticipate unknown target numbers by the strategy of maximizing their learning progress which adapt their prediction capabilities through active learning. The learning progress ofa specific subject to achieve exploratory and exploitative learning is converted into quantitative data by LPM algorithm and evaluated through the process.

B. Subjects

154 R&D engineers from 40firms in Taiwan are selected randomly as the subjects of the experiment in this study. Three to five engineers are selected randomly from each firm and all the involved R&D engineers participate new product development in their firms accordingly. Those 40 firms are classified into three industries named traditional manufacturing, high-tech manufacturing, and software design industry according to their individual business contents. The distribution of subjects for every industry is presented in Table 1.

Table 1. The distribution of subjects

	Quantity of firms	Quantity of Subjects
Traditional MFG	17	66
High-Tech MFG	14	57
Software Design	9	31
Total	40	154

C. Mechanisms of Experiments

Subjects are requested to anticipate target numbers from number 1 to 200. The target numbers are allocated in the unknown target zone which contains three continuous numbers. The mechanism of anticipation is shown below:

1) 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.
2) Strategies of anticipation: There are two strategies to approach anticipation which are "exploratory random generation" and "exploitative approach". The strategy of exploratory random generation, $M_{exploratory}$, defined as the individual subject picksthe number generated by the computer randomly, which simulates exploratory learning. The strategy of exploitative approach, $M_{exploitative}$, defined as the individual subject induces the numbers based on evaluatinglearning progress, which simulates exploitative learning.
3) Evaluation of learning progress: The values of learning progress and cumulative learning progress are calculated according to LPMalgorithm and provided to subjects for reference in every anticipation step.
4) Decision making of the anticipation: An individual subject predicts a number corresponding to the learning progress and the cumulative learning progress. The subject adopts either $M_{exploitative}$ or $M_{exploratory.}$

D. LPM Algorithm

According to the previous study of Chuang, Chang, and Hsu [31], LPM algorithm evaluates the learning progress by calculating the decrease of learning errors between two continuous learning steps according to the definition of Kaplan and Oudeyer [33]. However, the complex demands of today's innovation contexts indicate the need of integrating exploratory and exploitative learning [15] to simultaneously pursue both exploitative and exploratory innovations [12]. Therefore, the comparative learning progress ratio between exploitative learning progress and exploratory learning progress is defined to be the core concept of LPM algorithm [31]. In principle, a larger learning progress suggests more LPM reward will be received [33]. LPM algorithm [31]is defined as following:.

In the innovation process, a subject receives an input signal from previous situations and then predicts an output signal *O (n)* corresponding to his or her anticipations at any step n according to the innovation context. The 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.

The entire situation is summarized as *OR (n)*. The subject determines (or anticipates) *O (n)* based on previous situations *OR (n-1)*, *OR (n-2)*,…. Then the subject takes the current situation *OR (n)* as an input and tries to predict the future situation *OR (n+1)*. At specific step n, once *OR(n)* is defined, the subject learns in order to maximize the amount of cumulative rewards received. In the other word, 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).

$$e(n) = |\, O(n) - T \,| \qquad (1)$$

In the meantime, the LPM reward *R (n)* is also calculated. 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. Corresponding equations are represented as equation (2) and (3):

$$p(n) = e(n-1) - e(n): \quad e(n) < e(n-1) \qquad (2)$$

$$p(n) = 0: \quad e(n) \geqq e(n-1) \qquad (3)$$

In the case when learning progress is the only variable to maximum, the LPM reward *R (n)* equals to learning progress *p(n)*. Therefore, the equations (2) and (3) shown above are revised as equations (4) and (5) accordingly:

$$R(n) = p(n) = e(n-1) - e(n): \ e(n) < e(n-1) \qquad (4)$$

$$R(n) = p(n) = 0: \ e(n) \geqq e(n-1) \qquad (5)$$

In each step, the cumulative learning progress*P (n)* is computed as the integration over time of previous learning progress *p(n)* or LPM rewards *R (n)*. The cumulative learning progress *P (n)* is represented as equation (6):

$$P(n) = \Sigma^{n}_{j=1} p(n) = \Sigma^{n}_{j=1} R(n) \qquad (6)$$

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 comparative learning progress ratio *RP (n)*is defined as equation (7). The cumulative exploitative learning progress $P_{exploitative}$ *(n)* obtained for a specific subject who choosesexploitative learningat step n and the cumulative exploratory learning progress$P_{exploratory}$ *(n)* obtained for a specific subject who choosesexploratory learning at step n are compared simultaneously and systematically to come out the comparative learning progress ratio *RP (n)*.

$$RP(n) = P_{exploitative}(n) / P_{exploratory}(n) \qquad (7)$$

The cumulative learning progress *P (n)* equals to the cumulative LPM reward according to equation (6). Therefore, the comparative learning progress ratio *RP (n)* equals to the comparative LPM reward ratio *RR (n)*. Equation (7) is revised as equation (8):

$$RP(n) = P_{exploitative}(n) / P_{exploratory}(n) = \Sigma^{n}_{j=1} R_{exploitative}(n) \,/\, \Sigma^{n}_{j=1} R_{exploratory}(n) = RR(n) \qquad (8)$$

Considering the mathematics divergence issue on equation (8), a dummy number 0.01 is added on initial $P_{exploratory}$ *(n)* and initial $P_{exploitative}$ *(n)*automatically.

E. LPM Curve and LPM Characteristic Curve

According to the study of Chuang, Chang, and Hsu [31], the comparative learning progress ratio is generated at specific step n. A two-dimensional point is defined on the X-Y axis which takes step number n as the horizontalaxis (X-axis) and the comparative learning progress ratio *RP(n)*as the vertical axis (Y-axis). The curve, named LPMcurve,is constructed by connecting the points generated from all steps of anticipation. Therefore, each individual subject has his or her unique LPM curve through the innovation process. Then the LPM characteristic curve is generated by conducting multi-factor linear regression on the specified LPM curves. In the other word, the LPM characteristic curve represents the overall learning characteristic of the specified subjects.

IV. RESULTS

Through the experiment, the process-phase data generated by 154 subjects is recorded and converted by LPM algorithm into 154 individual LPM curves. LPM curves generated by the subjects are classified into several specific groups in which are classified by the unique complementarity characteristic between exploitative and exploratory learning. The unique complementarity characteristic is represented as the similarity of the LPM curve modal, which is identified through the specific group of LPM curves. Then the specific group of LPM curves, classified as the specific group, are converted into a LPM characteristic curve accordingly. Therefore, the specific curve modal of the LPM characteristic curve is classified as a specific learning type accordingly which represents the unique evolutionary interaction relationship between exploitative and exploratory learning.

A. Learning Type

154 individual LPM curves are classified into three groups based on the similarity of curve modal, which

refers to Group A, B, and C accordingly (refer to Fig. 1, 2, and 3).

Refer to Table 2, 42 subjects (27.3%) are classified as learning type A, 47 subjects (30.5%) as learning type B, and 65 subjects (42.2%) as learning type C.

The distribution of learning types for three industry types is summarized as followings:

1) Traditional manufacturing industry: 43.9% of the subjects are classified as learning type C, which is the main learning type for the subjects from traditional manufacturing industry. The distribution percentage of learning type A and B is quite similar.
2) Hi-tech manufacturing industry: 40.4% of the subjects are classified as learning type B, which is the main learning type for the subjects from hi-tech manufacturing industry. The distribution percentage of learning type A and C is similar.
3) Software design industry: 58.1% of the subjects are classified as learning type C, which is the main learning type for the subjects from software design industry. The distribution percentage of learning type A and B is similar.

Table 2: Distribution chart - industry types vs. learning types

	Learning Type A		Learning Type B		Learning Type C	
Tradition MFG	19	28.8%	18	27.3%	29	43.9%
Hi-Tech MFG	16	28.1%	23	40.4%	18	31.6%
Software design	7	22.6%	6	19.4%	18	58.1%
Total	42	27%	47	31%	65	42%

B. Learning Type A – Exploitative Learning Preferred

For the specific 42 subjects classified in Group A, the evolution of the comparative learning progress ratio *RP(n)*of the LPM characteristic curve (refer to Fig. 1) indicates that the subjects prefer to perform exploitative learning more often than exploratory learning which results in maintaining the value of *RP(n)*at the range of 1.5 ~ 1.2 up to 45 steps. From the 45th step up to the 65th step, exploratory learning is used by the subjects more often than exploitative learning which results in declining LPM characteristic curve. After the 66th step, the subjects achieve an equilibrium balance between exploitative and exploratory learning which results in closing to a flat LPM characteristic line. In this study, the learning type for the subjects classified as Group A is named learning type A which represents the characteristic of exploitative learning preferred.

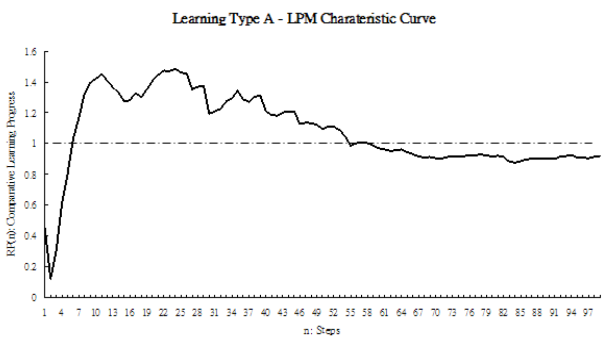

Fig. 1. Learning type A – LPM characteristic curves
note: LPM (Learning progress Motivation)

C. Learning Type B – Exploratory Learning Preferred

For the specific 47 subjects classified in Group B, the evolution of the comparative learning progress ratio *RP(n)*of the LPM characteristic curve (refer to Fig. 2) indicates that the subjects prefer to perform exploratory learning more often than exploitative learning which results in maintaining the value of *RP(n)* below 1.0. The upward tilted LPM characteristic curve which is below the line of *RP(n)* = 1.0 represents more exploratory learning is applied than exploitative learning but the influence of exploratory learning is decreasing gradually through the innovation process up to the 68th step. After the 69th step, the subjects achieve an equilibrium balance between exploitative and exploratory learning which results in closing to a flat LPM characteristic line. In this study, the learning type for the subjects classified as Group B is named learning type B which represents the characteristic of exploratory learning preferred.

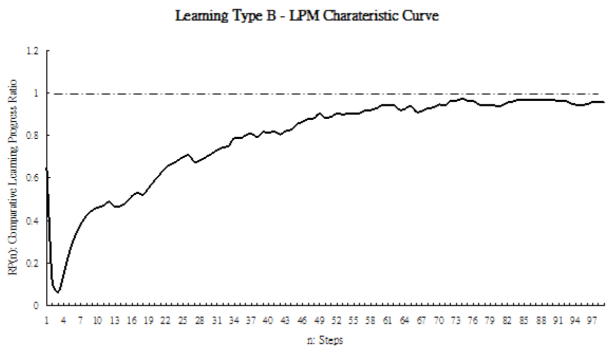

Fig. 2. Learning type B – LPM characteristic curves
note: LPM (Learning progress Motivation)

D. Learning Type C – Blended Exploitative & Exploratory Learning

For the specific 65 subjects classified in Group C, the evolution of the comparative learning progress ratio *RP(n)*of the LPM characteristic curve (refer to Fig. 3) indicates that the subjects achieve a balance between exploitative learning and exploratory learning through the entire innovation process. The wavy modal of the LPM characteristic curve represents that the subjects shift the utilization of exploitative and exploratory learning often. Especially the value of *RP(n)* changes sharply from 0.3 to 2.25 and then drops down to 0.75 in the first 30 steps of the innovation process, which represents high utilization rate of exploratory learning at the initial phase (up to the 10th step) of innovation process. And then shifts from high utilization rate of exploratory learning to high utilization rate of exploitative learning from the 11th step to the 30th step. Following by the sharply change, the value of *RP(n)*maintains at a narrow range of 0.75 ~ 1.0 with comparative smooth wavy progress. Not similar to learning type A and B, an equilibrium balance between exploitative and exploratory learning is not taken place through the entire innovation process for learning type C.

Therefore, the subjects of learning type C expedite innovation progress (that is, the rate reaching the line of $RP(n) = 1$) by excessively utilizing exploratory learning at the initiation phase and then shift to excessive exploitative learning right after the initiation phase. For the rest of innovation process the subjects of learning type C keep well balance between exploitative and exploratory learning under high-low level combination in order to sustain a wavy curve which keeps moving up and down along the line of $RP(n) = 1$. In this study, the learning type for the subjects classified as Group C is named learning type C which represents the characteristic of blended exploitative and exploratory learning.

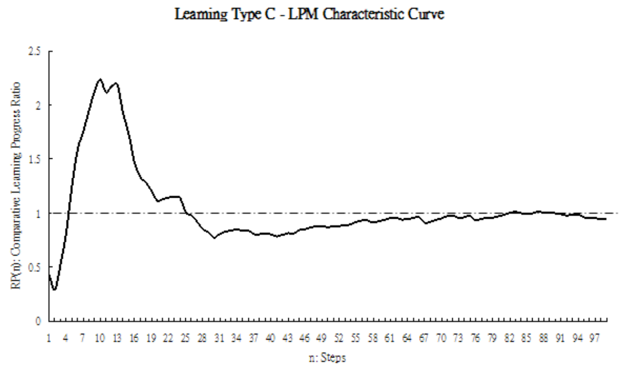

Fig. 3. Learning type C – LPM characteristic curves
note: LPM (Learning progress Motivation)

V. Discussions

A. The Characteristic of Learning Types

The trend curve of the LPM characteristic curve for each learning type is generated by using 6th order polynomial regression, which represents the specific modal of the LPM characteristic curve for the corresponding learning type. The trend curves for learning type A, B, and C are shown in Fig. 4.

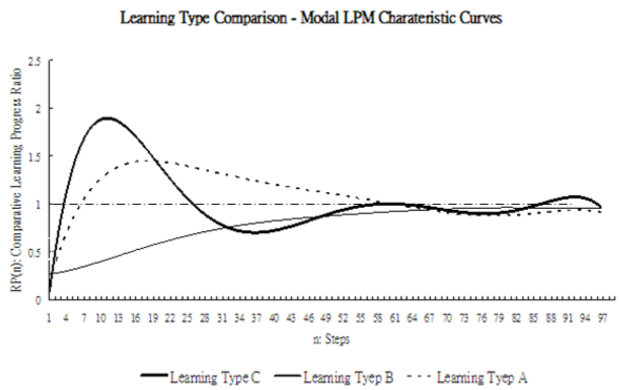

Fig.4. Learning type comparison – modals of LPM characteristic curves
Note: LPM (Learning progress Motivation)

B. Learning Deactivation – Learning Type A > Type B > Type C

Refer to the process-phase records of the LPM characteristic curves for three learning types, all LPM characteristic curves except the one for learning type C reach the steady-state condition [31]at the 66th step (for learning type A: refer to Fig. 1 and 4) and 69th step (for learning type B: refer to Fig. 2 and 4). In the LPM characteristic curve study [31], the steady-state condition of the LPM characteristic curve is defined as the LPM characteristic curve nearly parallels the line of $RP(n) = 1$. Hence, subjects tend to reach an equilibrium balance between exploitative and exploratory learning and approach a stationary comparative learning progress ratio $RP(n)$ in the steady-state condition. Furthermore, the steps taken for anticipating the target number reach a constant under the steady-state condition [31], which represents subjects' learning tends to saturate gradually and reaches a certain deactivation status. Chuang, Chang, and Hsu [31]defines such phenomenon as learning deactivation in the steady-state condition.

According to the findings of this study, the LPM characteristic curve for learning type A reaches learning deactivation at the 66th step which is earlier than the LPM characteristic curve for learning type B at the 69th step. Comparing with the LPM characteristic curves for learning type A and B, the LPM characteristic curve for learning type C does not have obvious learning deactivation because the steady-state condition has not taken place in the innovation process. Refer to Fig. 4, the significant wavy condition takes place once the trend curve of LPM characteristic curve for learning type C reaches the line of $RP(n) = 1$. However, such wavy condition has not been taken place for the trend curves of LPM characteristic curves for learning type A and B. In summary,

1) The subjects of learning type A reach learning deactivation earlier than the subjects of learning type B in the innovation process.
2) The subjects of learning type C do not have obvious learning deactivation, which secured sustainable learning through the innovation process by the blended exploitative and exploratory learning.

C. Innovation Deactivation – Learning Type A > Type B > Type C

In the LPM characteristic curve study (Chuang, Chang, & Hsu, 2012), the subjects are motivated effectively and continuously by LPM to pursue maximal learning progress and result in continuously improving innovation performance. But such continuous improvement progress tends to saturate gradually and reaches a deactivation status in the steady-state condition, which is defined as innovation deactivation. The innovation deactivation is in line with the progress of learning deactivation in the steady-state condition. Refer to Fig. 4, the findings of this study indicate the similar situation as the study of Chuang, Chang, and Hsu[31].

The findings of this study indicate:

1) The steady-state condition has taken place for the subjects of both learning type A and B, which results in innovation deactivation.

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2) The subjects with the exploitative learning preferred characteristic (learning type A) reach innovation deactivation earlier than the subjects with exploratory learning preferred characteristic (learning type B).
3) The steady-state condition has not taken place for the subjects with the characteristic of blended exploitative and exploratory learning (learning type C) and results in no innovation deactivation; furthermore, the subjects with the characteristic of blended exploitative and exploratory learning (learning type C) keep pursuing higher innovation performance which secures sustainable innovation.

D. Sustainable Innovation

There are a few implications to be identified from the results of this study. Refer to Fig. 1, 2, 3, and 4, especially the trend curves shown in Fig. 4, both the LPM characteristic curves of learning type A and B approach the steady-state condition, which close along the line of $RP(n) = 1$, through a slow step-by-step gradual process that can be identified by the modal of the LPM characteristic curves and trend curves of learning type A and B. On the other hand, the LPM characteristic curve and the corresponding trend curve of learning type C approach the line of $RP(n) = 1$ much quicker (starts from the 49th step and the first touch is even earlier at the 25th step) than the LPM characteristic curves of learning type A (starts from the 66th step) and B (starts from the 69th step). However, the LPM characteristic curve and the corresponding trend curve of learning type C never end up with steady-state condition. Refer to Fig. 4, the trend curve of learning type C moves up and down along the line of $RP(n) = 1$, which is totally different from the curve modals of learning type A and B.

In summary,
1) Comparing with the exploitative learning preferred (learning type A) and exploratory learning preferred (learning type B) characteristic, the characteristic of blended exploitative and exploratory learning (learning type C) facilitates effective innovation through well balance between exploitative and exploratory learning under high-low level combination according to the innovation context through the entire innovation process, which is in accordance with Li's findings[37].
2) Extending the dynamic view of ambidexterity [35]-[36]into innovation process where managing the exploitative and exploratory learning activities should temporarily cycle through periods of exploitation and exploration. This indicates that innovation becomes successful through temporal sequencing of routines for exploitation and exploration learning depending on different demands of innovation context, thus engaging primarily in only one learning at a time based on the specific innovation context [37]. Therefore, the innovation context enable the modes of exploitative and exploratory learning to be adjusted accordingly in order to overcome the challenges of simultaneously managing exploitative and exploratory learning in the innovation process when the two distinct learning strategies compete for scarce resources.
3) The most valuable characteristic of blended exploitative and exploratory learning is to stay away from learning deactivation and innovation deactivation which have taken place on the subjects with either exploitative learning preferred or exploratory learning preferred characteristic.
4) How to stay away from learning deactivation and innovation deactivation to keep improving innovation performance is however the most valuable competence. Therefore, the subjects with the characteristic of blended exploitative and exploratory learning have the most optimal competence with maintaining sustainable innovation.

VI. CONCLUSION

The process-phase time-frame based data generated by 154 individual subjects is converted by LPM algorithm into 154 LPM curves and classified into three groups based on the similarity of curve modal, which represented as Group A, B, and C. Three LPM characteristic curves are generated for three groups of LPM curves, which represents the characteristic of learning type for each specific group of subjects correspondently. The comparative learning progress ratio between exploitative and exploratory learning for the subjects of specific learning type is identified through assessing the corresponding LPM characteristic curve, which represents subjects' characteristic in the interaction of exploitative learning and exploratory learning and how the influence of specific learning type is on the innovation at process-phase time-frame based exploration. According to the findings,

1) Learning type A represents the subjects with exploitative learning preferred characteristic, which represents excessive exploitative learning.
2) Learning type B represents the subjects with exploratory learning preferred characteristic, which represents excessive exploratory learning.
3) Learning type C represents the subjects with the characteristic of blended exploitative and exploratory learning, which represents well balance between exploitative and exploratory learning under high-low level combination.

In the LPM characteristic curve study [31], learning deactivation and innovation deactivation take place when subjects reach the steady-state condition. According to the findings of this study,
1) The subjects of both learning type A and B reach steady-state condition at minor different steps in the innovation process. The subjects of learning type A are earlier than the subjects of learning type B reaching steady-state condition. Therefore, the subjects of learning type A and B all experience learning deactivation and innovation deactivation. In the other word, the subjects with either exploitative learning preferred or exploratory learning preferred characteristic experience learning deactivation and innovation deactivation in the innovation process. That is, the subjects of either excessive exploitative learning or excessive exploratory learning characteristic experience learning deactivation and innovation deactivation in the innovation process.

2) The subjects of learning type C has different experience from the subjects of learning type A and B. There is no obvious steady-state condition taken place on the subjects of learning type C; therefore, neither learning deactivation nor innovation deactivation is taken place on the subjects of learning type C. In the other word, the subjects with the characteristic of blended exploitative and exploratory learning sustain innovation in the entire innovation process.

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