

**A Market-Based Computational Approach to Knowledge Acquisition
for Organizational Learning**

(Academic Track)

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I. INTRODUCTION

An organization learns as its members interact dynamically with each other or with the organization's external environment, and experiences resulting from this dynamic interaction lead to more successful performance. In an organization, employees are the major source of knowledge, and these knowledge agents interact with each other for acquiring knowledge, via sharing or exchange, in accomplishing organizational goals or objectives. The interaction among knowledge agents can be likened to a knowledge market in which various kinds of knowledge transactions take place. Through knowledge transactions, there will be a re-distribution of knowledge "wealth" in an organization. We conceptualize organizational learning as a manifestation of the collective learning behavior of knowledge agents in an organization.

In order to investigate the emergent learning behavior of an organization, we propose a market-based model for facilitating knowledge acquisition and exchange in an organization. In our computational model each agent has its own knowledge wealth and associated reputation. The reputation of an agent is a measurement of an agent's contribution to the organization as perceived by its peer agents. With our market mechanism, buyers look for reputable expert agents and pay prices for acquiring knowledge for the completion of organizational tasks or producing the knowledge needed by other agents. Knowledge offered by different knowledge-selling expert agents has different value to buyers, reflecting how greatly it is wanted by the rest of the market. Each transaction will accordingly increase the reputation of the knowledge-selling expert agents involved in the transaction. We assume each agent in our market always strives to

maximize its net revenue which is a reflection of its reputation in the organization. Through our simulated computational knowledge market, we attempt to facilitate the understanding on the mechanisms that enable organizational learning as an emergent phenomenon of interaction, either competition or collaboration, among knowledge agents of an organization.

II. KNOWLEDGE MARKET, TACIT KNOWLEDGE and COLLABORATIVE ORGANIZATIONAL LEARNING

In a knowledge market one might find several buyers, sellers and brokers of knowledge. Knowledge buyers are those who are seeking to resolve complex issues that have no easy answers. They look for insights, judgments, and understanding that will make them more successful in their work. Knowledge sellers are those who are reputed to have substantial knowledge about a particular process or subject. These individuals are not always in plain view because they may be reluctant to share what they know or they may feel that their true power resides in the knowledge they hold. This lack of potential fair exchanges of knowledge presents one of the greatest obstacles to knowledge selling. Brokers are the facilitators. The brokers make connections between the buyers and the sellers. Usually, brokers play a key role in the exchange of knowledge in an organization because of their ability to span geographic, organizational, and departmental boundaries.

In each knowledge transaction, buyer agents interact directly, or via knowledge brokers, with seller agents in obtaining or exchanging the needed knowledge for improving the performance in accomplishing organizational tasks. According to Simon (1983), learning results in adaptive changes in a system that enables the system to do the same task or similar tasks more effectively the next time. Knowledge transactions result in individual learning, and

organizational learning is actually an emergent phenomenon of knowledge re-distribution among knowledge agents via knowledge transactions. Organizational learning will in turn facilitate more knowledge transactions in a continuous and mutual interaction manner (Argyris and Schön, 1996), and knowledge will be re-distributed optimally through these interactive, iterative processes. Fundamentally, organizational learning is a multi-stage optimization process (Day, 1975).

Boisot (1995) classifies organizational knowledge, along the dimensions of codification and diffusion, into: the codified yet undiffused proprietary knowledge, the uncoded and undiffused personal knowledge (also referred to as tacit personal knowledge, the codified and diffused public knowledge, and the uncoded yet diffused commonsense knowledge. In this paper we focus on the tacit personal knowledge. Tacit personal knowledge is the implicit knowledge that organizational members learned through years' of experience in performing organizational tasks, and is distributed in the totality of the individual's experience. This type of knowledge is hard to verbalize and cannot be reduced to rules or standard operating procedures. This type of personal, tacit knowledge underlies organizational capabilities (Winter, 1994), and is vital to organization learning, for organizations can only learn and innovate by leveraging on the tacit knowledge of their members (Choo, 1998).

Though traditional research on organizational learning assumes individual mastery and acquisition of the knowledge needed for accomplishing the task, many studies indicate that knowledge in organizations is often tacitly shared by members of communities of practice, and exists in the distinct practices and relationships that emerge from the coordinated accomplishment of tasks over time (Badaracco, 1991; Brown and Duguid, 1991; Orr, 1990; Wenger, 1991). Similarly, March (1981) proposes his model of decision making in

organizations, for which he sets aside the assumption of a single or unified decision maker, developing instead the concept of a loose and shifting “coalition” that selects or accomplishes organizational goals. In a coalition or community of practice, each member possesses partial but complementary knowledge, so that only the team working together as a whole has the full body of knowledge (Badaracco, 1991). The tacit knowledge can be possessed by members of a team or an organization to the effect that they know which agents in the organization have the expertise in certain areas (Winter, 1987). Organizational learning is exhibited as the change of organizational processes for accomplishing tasks through the collaborative work of members of a coalition (March and Olsen, 1976). It has been shown that collaborative learning usually results in a higher efficiency compared to individual learning (Lin and Yao, 1998; Tan, 1993).

The above thoughts have been incorporated into the design of our conceptual model. In our conceptual model, a task will be accomplished through the cooperation of a group of experts forming a coalition (or a community of practice) and working on the task in a sequential manner. Membership of the coalition is subject to change, through the market mechanism, according to the contribution each member made toward the task accomplishment, and this membership modification over time can be regarded as the change of organizational processes. Therefore, an organization learns through the modification of membership for the community of practice or coalition in achieving organizational goals over time.

III. A MARKET-BASED COLLABORATIVE MODEL FOR ORGANIZATIONAL LEARNING

We regard learning as a collective process of interaction among agents in an organization. In this paper we model an artificial organization which consists of agents collaborating in

accomplishing tasks. In this organization, the information needs of buyer agents are mediated through the broker agent to a group of expert agents. Through competition, the winner agents will have the privilege of providing their expertise or services to buyer agents, and winner agents will receive rewards from buyer agents as shown in Figure 1. In addition, winner agents will also receive rewards from the organization as an incentive for knowledge sharing.

Our conceptual model is designed for the environment where the completion of the task requires the collaborative application of tacit knowledge of organizational members, and each

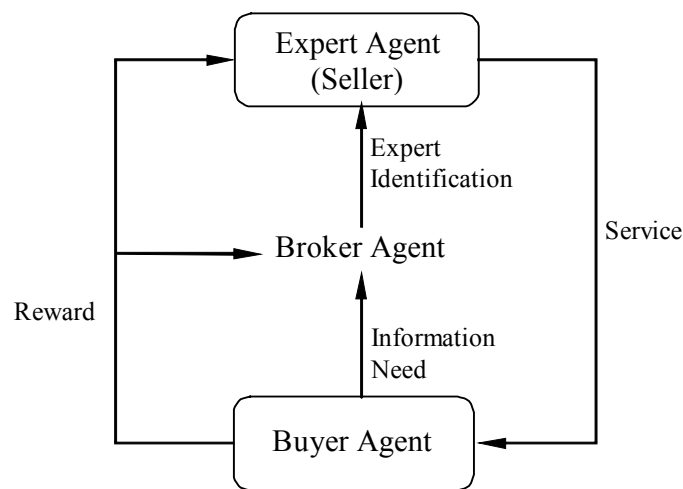


Figure 1. A market-based relationship among agents.

member alone does not have enough knowledge to complete the task. In addition, in a collaborative learning environment, agents are not required to learn everything from their own experiences and to complete their tasks on their own. Usually, the completion of a task needs a chained series of consultation with expert agents for task completion. Still, each expert agent might need to “outsource” part of its work to other expert agents due to insufficient knowledge for the task. Through identifying qualified expert agents whose expertise can complement the buyer (or learning) agent’s insufficient knowledge, a team or coalition of agents will emerge to accomplish the task.

During the coalition formation process, expert agents are selected for participation based on their strength representing their reputation or performance for problem solving. Our model is for multiple-step learning tasks. Tasks will be completed through the collaboration among experts in the sense that they form a chain of “upstream-downstream” working relationship with each contributing to part of the task completion. Through the modification of agent strength, an organization learns more efficient chains of agents for accomplishing the tasks over time. Ahmadabadi and Asadpour (2002) proposed a computational agent model for single-step learning tasks, and the performance of each agent is measured by its “expertness” which is a value on which a buyer or learning agent would base in selecting the expert agents. The value for “expertness” is based on the reinforcement signals and the number of moves in reaching the goal. In our knowledge market, each agent has its own capital, which is a measurement of the agent’s strength in making contributions to the organization. The capital of an agent can be measured in terms of factors, such as reputation, willingness to share, time for completing a task, and capacity. Through the transactions in the knowledge market, an agent’s capital will change stochastically over time.

Our conceptual model is proposed in Figure 2, which is an adaptation of the model proposed in Deng, *et al.* (1990). We assume our organization is a task-oriented organization. When a task is announced, there is a knowledge discrepancy for fulfilling the task. Broker agents are the “middlemen” who know which agents have expertise in certain areas. According to Winter (1987), this task-expert connection knowledge is a type of organizational tacit knowledge. Broker agents help identify a group of qualified expert agents for the need of the task. This group of agents will compete with each other to offer its expertise to contribute to the completion of the tasks. The winning agent will be selected by the Expert Selection Process.

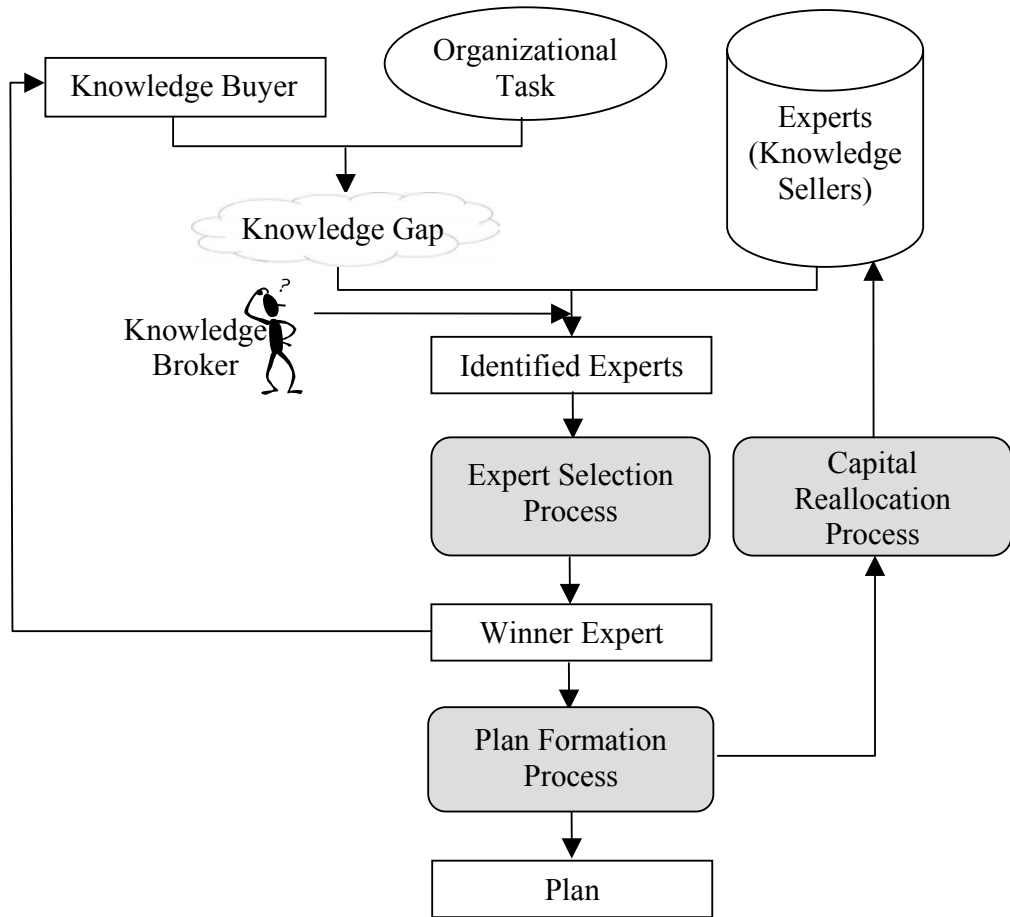


Figure 2. A knowledge market model for collaborative organizational learning.

The complexity of the task might entail the winning agent to seek help or advice from the other agents in complementing its own knowledge, and thus initiate the next cycle of agent selection. This process will result in an “upstream-downstream” collaborative relationship among agents, and a coalition of agents will emerge. This is similar to the formation of a strategic alliance among agents. Since each agent represents its own tacit knowledge, the “upstream-downstream” collaborative relationship among agents can also be regarded as the formation of a plan for the task. Our model is characterized by the expert agents (or seller agents) competing with each other locally to become a winner, while buyer agents collaborate with each other globally in forming a plan for task accomplishment.

“Downstream” agents will reward “upstream” agents for their services. The final plan is subject to organizational evaluation in terms of how effective it is in achieving the tasks, and participants of this plan will be rewarded for their contributions. The rewarding functions are performed by the Capital Reallocation Process, and will result in the adjustment of agent capitals. This capital reallocation will affect the competitiveness of agents in participating in the organizational market for future tasks. Based on the evaluation of the plan, the next cycle of plan formation will be initiated for the modification of the first plan, and improvement on the performance for task accomplishment will gradually develop.

The adjustment of agent capitals via the Capital Reallocation Process will enable the organization to learn at both the local level, in the sense that better agents will be chosen from each local competition next time when the same task is to be performed, and at the global level, in the sense that a better plan for the task will emerge through the improved performance at the local level. Since a plan can be regarded as a strategy for tackling an organizational task, generation of a new plan (or strategy) at the global level through the improved performance at the local level is the indication of double-loop learning (Argyris and Schön, 1996) in our organization.

III.1 Expert Selection Process

This is the mechanism for selecting a winner agent to participate in forming the coalition or plan for achieving the task. This process incorporates various attributes of the agent into consideration so that agents not strongest on a particular attribute can also be considered. This is a fairer selection process, especially for the new agents who have not yet made contributions to the organization. Since the capital of each agent is the accumulated result of the contribution an agent made to an organization over time, it is an indicator of the relative strength or importance

of each agent in the organization. Based on the strength of each agent, a probability distribution can be generated for selecting agents to participate in solving the problem. This process of winner agent selection is shown in Figure 3.

This expert selection process is initiated by the information need for filling the knowledge gap for accomplishing the organizational task. A group of experts is attracted to compete for serving this need. Attributes of the agent will be used as the initial selection criteria, and each attribute has a probability of being applied as a selection criterion. Therefore, application of each attribute will probabilistically generate a subset of experts. Any two subsets generated from two different attributes are not necessarily disjoint. In other words, some agents may be included in multiple subsets of agents. Each agent in a subset has a probability of being selected. We can obtain a weighted strength for each agent based on the strength of each agent and the probability sum for that agent to be selected from all the subsets. The weighted strength of each agent is an indicator of the potential for that agent to be selected from the entire set of agents participating in the competition, and the winner agent has the highest weighted strength.

III.2 Plan Formation Process

Due to the complexity of the task, it usually requires the collaboration among agents for task completion. An agent alone does not have enough knowledge to complete the entire task. This new knowledge gap will trigger the next cycle of expert selection. The winner agent generated from the previous cycle becomes the knowledge buyer this time, and it will “outsource” its information need to a group of competing expert agents (i.e., knowledge sellers). The knowledge buyer will pay the winner agent as selected by the Expert Selection Process. In turn, the new winner agent will become the knowledge buyer in the next cycle. This process will continue until the task is completed.

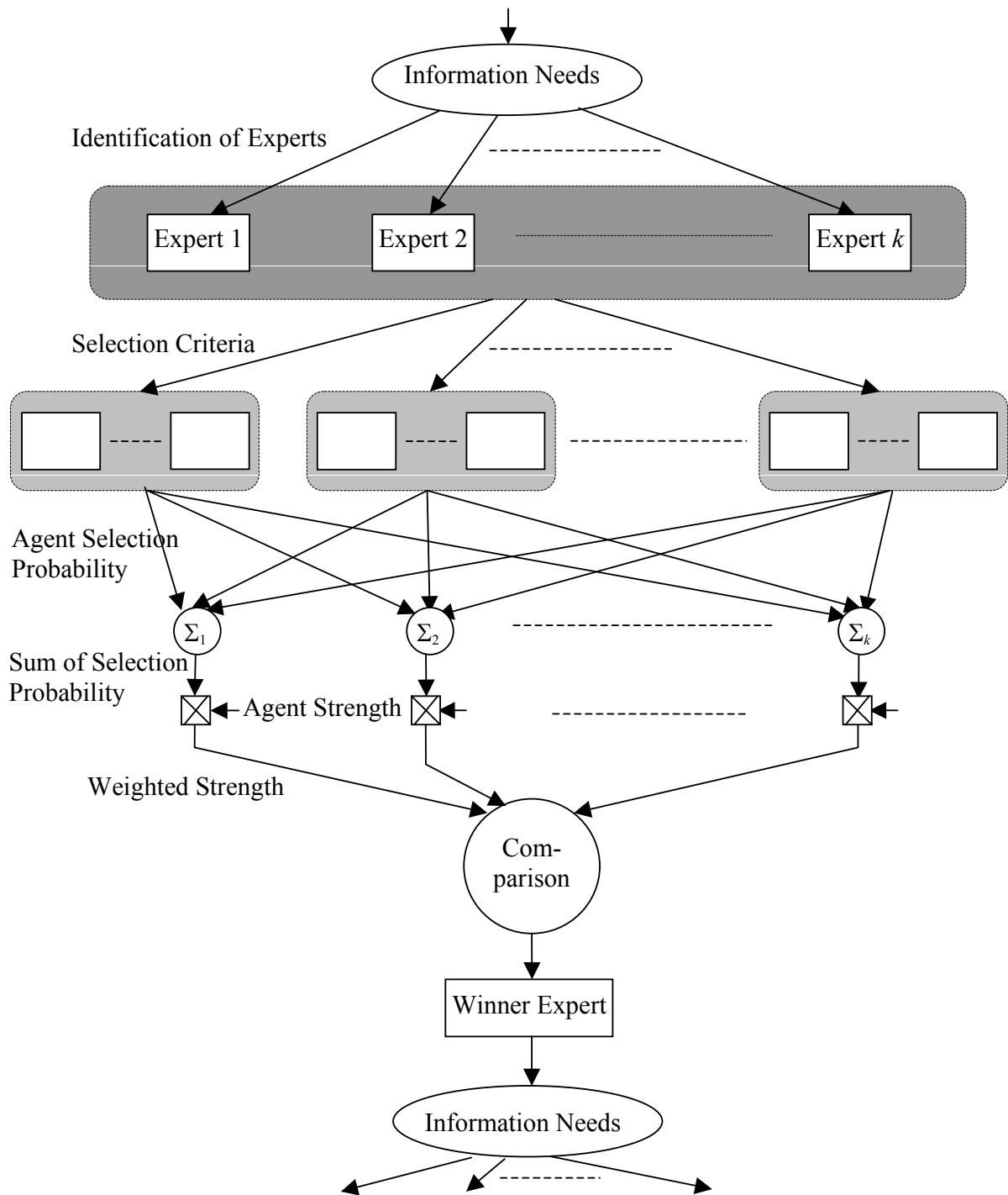


Figure 3. Expert selection process.

During this process, expert agents compete locally with each other to become a winner, while winner agents collaborate globally with each other to accomplish the task. The global collaboration among winner agents leads to the formation of a coalition through a chained relationship, which is similar to a series of “upstream-downstream industries”, among winner agents. Since each agent representing its tacit knowledge, agents in the coalition can be regarded as forming a plan for accomplishing the task. This Plan Formation Process is shown in Figure 4.

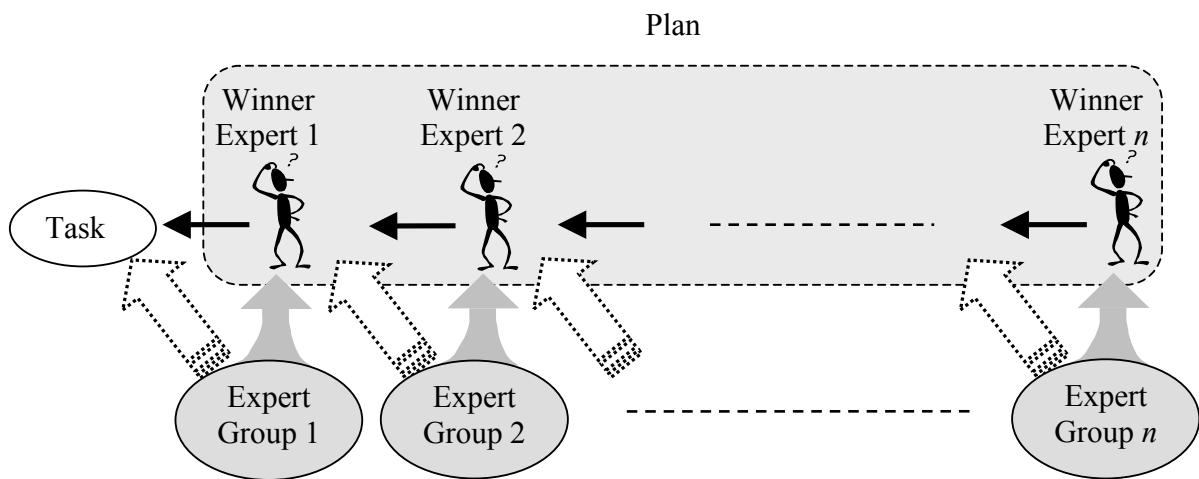


Figure 4. The plan formation process.

III.3. Capital Reallocation Process

The Capital Reallocation Process provides the market mechanism in modifying the capital for each agent. The capital of an agent can be regarded as its strength, and is the portfolio of attributes, such as reputation, credit, goodwill, and capability. Modification of an agent’s capital will affect the competitiveness of the agent in participating in the knowledge market for future tasks. In turn, this capital modification will also affect the potential for an agent to

participate in the global collaboration for plan formation. Actually, the Capital Reallocation Process underlies both the Expert Selection Process and the Plan Formation Process.

This process modifies agent capital at both the local and global levels. In each transaction taking place in our knowledge market, the winning seller agent generated from local competition has the privilege to provide service to satisfy the immediate need of the buyer agent, and receives the rewards from the buyer agent. Through this local transaction, the capital of the buyer agent and the seller agent will be changed. At the global level, the plan formed through the collaboration among winner agents will be evaluated for the effectiveness in fulfilling the organizational task. Rewards will be assessed to this coalition of winner agents as a form of feedback on its performance in achieving the task. Rewards at the global level will also change the capital distribution of agents in the organization. It is the capital adjustment and reallocation function that enables our organization to exhibit the double-loop learning behavior.

In our proposed knowledge market the capital of each agent is defined as a portfolio of n attributes: $\mathbf{S} = \{s_1, s_2, \dots, s_n\}$, where s_i is the i^{th} attribute or characteristic of an agent. Capital of an agent affects the probability p of that agent to be chosen. A micro-view of the capital reallocation-driven double-loop learning is provided in Figure 5, which is an adaptation of the model proposed in Deng (1996). Note that only capital-adjustment related functions are included in Figure 5.

At each transaction stage, the Agent Evaluation function generates a payoff for the winner agent based on the capital distribution over a group of k competing agents $[p_1, p_2, \dots, p_k]$. This payoff will be employed by the Capital Transformation function to change the capital portfolio for both the buyer agent and the winner seller agent in the next cycle of transaction. In turn, this capital reallocation will initiate a modification of capital distribution

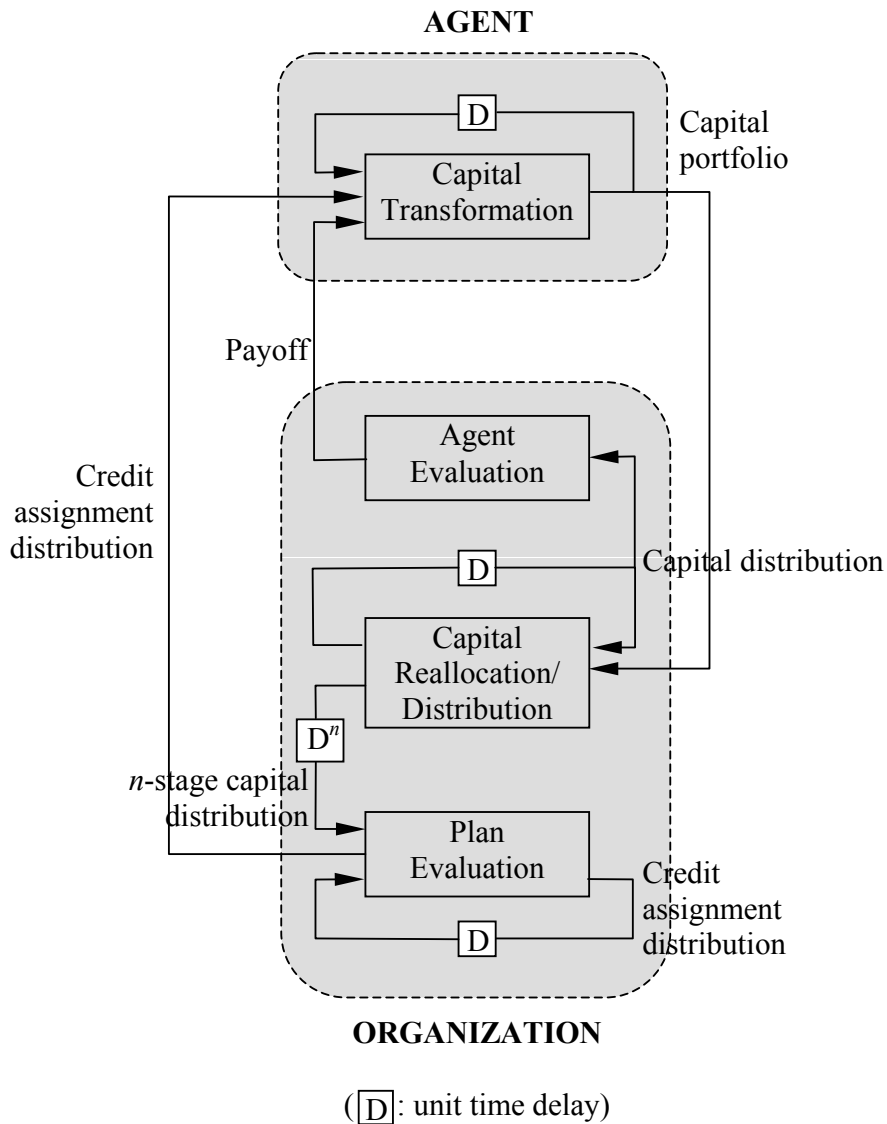


Figure 5. A capital reallocation-driven double-loop learning process.

over a group of agents through the Capital Reallocation/Distribution function. The modification of capital distribution underlies learning at the local level. Since a capital distribution over a group of competing agents at each transaction stage determines a winner agent, the capital distributions over n stages of transactions forms the basis for evaluating the plan generated from these n stages of competition. The Plan Evaluation function assigns credit to each plan or

coalition-participating agent. This credit assignment will be incorporated into the adjustment of the agent's capital for the next cycle of transaction. The credit assignment distribution over a group of agents will be adjusted after the cycle of transaction based on the new plan generated. The adjusted credit assignment distribution is the result of the accumulated experience from the knowledge transaction processes, and will affect the modification of the plan for the organizational task. Learning at the global level will emerge through the adjustment of the credit assignment distribution at each knowledge transaction cycle.

IV. SUMMARY

In this paper, we drew upon the concepts of knowledge market, organizational tacit knowledge, and organizational learning in proposing a market-based model for collaborative organizational learning. One of the basic assumptions for our model is a task-oriented knowledge market where agents competing and willing to offer their expertise for the accomplishment of organizational task. Through offering their expertise, agents will accumulate more "capital." This will enhance their competitiveness in the knowledge market for future tasks. Another assumption is that the completion of the task requires the application of tacit knowledge of organizational members. The other is that each organizational member alone does not have enough knowledge to complete the task. Organizational members need to collaborate together in accomplishing the task.

Our model is characterized by the local competition among seller agents and the global collaboration among buyer agents in forming a plan for task accomplishment. This feature is achieved through three closely coupled processes: the Expert Selection Process, the Capital Reallocation Process, and the Plan Formation Process. The Expert Selection Process allows the

winner agent to be selected through local competition. The Plan Formation Process connects together winner agents generated from each cycle of local competition in formulating a plan for task accomplishment. The Capital Reallocation Process provides the market mechanism in modifying the capital for each agent. The modification of agent capital, in turn, will affect the competitiveness of each agent in the local competition and the potential to participate in the global collaboration for plan formation. Through repetitive application of the above processes, an organization will be able to exhibit learning behavior in developing better plans for task execution over time. Further analysis of our model will be conducted in the near future.

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