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INCENTIVE STRATEGY FOR KNOWLEDGE TRANSFER IN ENTERPRISE VIA E-LEARNING 2.0

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Abstract. *As less attention has been paid to how effective knowledge transfer occurs through a variety of incentives for communication and collaborative learning, in this study, we examine the effects of different incentive strategies on the random distribution of absorption efficiency and dissemination capability. We address the research objective by developing a computational model for E-Learning 2.0 in a dynamic knowledge environment consisting of multiple distinct knowledge agents. Firstly, it is assumed that knowledge transfer via E-Learning 2.0 is stimulated by incentives. Secondly, E-Learners have unique knowledge attributes. Thirdly, the knowledge evolution model specifies the policy of knowledge transfer. Fourthly, feedback from the simulation model shed light onto the incentive mechanism. Overall, we find that dissemination capability is an important variable in determining the effectiveness of incentive strategies. High incentive strategies focusing on high rewards for active learning are the preferred option in most of the considered scenarios. Interestingly, increased efficiencies in absorption can facilitate better knowledge value and knowledge transfer. These findings indicate that firms facing longer knowledge life cycles, higher dissemination in knowledge transfer capacity and better absorption efficiencies actually confront more difficult challenges in knowledge transfer. We examine the effects of different incentive strategies on the random distribution of absorption efficiency and dissemination capability. The optimal incentives for knowledge transferring derived from the simulation results of the model are suitable for E-Learners with different knowledge characteristics.*
Keywords: Incentive strategy, Knowledge value, Knowledge transfer, E-Learning 2.0, Computational model

1. **Introduction.** In recent years, Web 2.0 has grown by featuring collaborative cooperation and knowledge sharing platforms. Web 2.0 aims to collect information from the entire population, rather than on a few experts, since information flow has changed from unidirectional to bidirectional. Web 2.0 has been applied to E-Learning as "E-Learning 2.0". Accordingly, E-Learning 2.0 is defined as the use of Web 2.0 to deliver a broad array of solutions that enhance knowledge and performance [3]. E-Learning 2.0 communities are useful in joining people with similar skills and interests to engage in informal interaction, support one another and provide meaningful advice and feedback regarding E-Learning tasks and topics of shared interest [15]. Therefore, E-Learning 2.0 is an important channel of knowledge transfer among E-Learners, which can be accomplished through interaction and collaborative learning.

Because knowledge transfer provides opportunities for collaborative learning, organizations are able to realize remarkable increases in performance through knowledge transfer. The empirical evidence indicates that organizations that transfer knowledge effectively are more productive and more competitive than those that do not. Although this knowledge-based theory of the firm views organizations as social communities that specialize in efficient knowledge creation and transfer, successful knowledge transfer is difficult to achieve [12]. Efficient knowledge transfer calls for a comprehensive understanding of knowledge recipients' absorptive capabilities and knowledge senders' disseminative capabilities.

For a knowledge intensive organization, the process of E-Learning encompasses the following three important and closely related elements: (i) participating in E-Learning, (ii) transferring knowledge via E-Learning, and (iii) maintaining a proper knowledge network among the existing workforce. Knowledge transfer has received much attention; however, previous studies that focused on the importance of cooperation in the process of knowledge transfer via E-Learning 2.0 identified the goals based on continuous interaction and knowledge sharing. The implicit assumptions are that both knowledge absorptive capacity and knowledge disseminative capacity are symmetrically distributed among E-Learners, and that knowledge can be transferred by E-Learners spontaneously. In reality, symmetrical distribution is an unusual scenario, and effective knowledge transfer occurs through a variety of incentives for communication and collaborative learning.

Hence, this study examines interactive effects of knowledge transfer incentives. We conduct simulations to illustrate the dynamics of incentives for knowledge transfer via E-Learning 2.0 given a set of rules. This study aims to answer the following research questions:

(1) Is it possible to encourage efficient knowledge transfer via E-Learning 2.0 with incentives?

(2) If so, how effective are the incentives provided for knowledge transfer via E-Learning 2.0?

The remainder of this paper is organized as follows. The next section presents the literature review. Then, we build the rules system of behavioral change and interactions among network members. Subsequently, the simulation results are analyzed. Finally, the discussion and conclusions are presented.

2. Literature Review.

Substantial barriers to knowledge transfer create difficulties and complications in transferring knowledge within the firm [1]. It was suggested that firms must establish routines and processes to acquire, assimilate, transform, and exploit knowledge and produce a dynamic organizational capacity [14]. This implies that knowledge transfer must span different knowledge holders and requires a collaborative effort on the part of both knowledge senders and recipients [20].

On the one hand, the absorptive capacity of knowledge recipients is a necessary condition for efficient knowledge transfer, but it is not sufficient. Absorptive capacity refers to identifying and recognizing the value of knowledge and information, absorbing and assimilating knowledge and information, and applying knowledge and information [7]. Accordingly, the knowledge recipients' knowledge state changes once they absorb new knowledge. Meanwhile, if knowledge holders do not have sufficient ability to transfer the needed knowledge to recipients, the efficiency and effectiveness of knowledge transfer are greatly reduced. Thus, knowledge senders' disseminative capacity is an important determinant of knowledge transfer [16,21]. Efficient knowledge transfer requires the strong disseminative capacity of knowledge senders. In this sense, knowledge disseminative capacity can be defined as the ability to efficiently, effectively and convincingly articulate and communicate, spread knowledge in a manner that other people can accurately understand, and tactically put the learning into practice.

On the other hand, although the E-Learning 2.0 environment [6] that integrates the features of Web 2.0 has great potential to innovate and improve the existing platforms, fostering social interaction learning [5], it cannot assure that people will be motivated to transfer special knowledge. Therefore, it is necessary to provide incentives, to encourage people to voluntarily transfer special knowledge. Knowledge incentive mechanisms, as the newest trend in knowledge management, aim to stimulate organizational innovation and allocate motivation in the most effective way [13]. Particularly within knowledge incentive mechanisms, high-powered performance incentives may adequately strengthen individual knowledge transfer behavior within an organization.

Thus, it is reasonable to believe that effects of incentives play pivotal roles in knowledge transfer via E-Learning 2.0. However, this idea is a conjecture rather than an empirically proven construct. Consequently, to capture the interactive nature of knowledge transfer via E-Learning 2.0, the current article introduces incentive effects into knowledge transferring via E-Learning 2.0.

3. **Research Frameworks and Research Methods.** The research framework is illustrated in Figure 1.

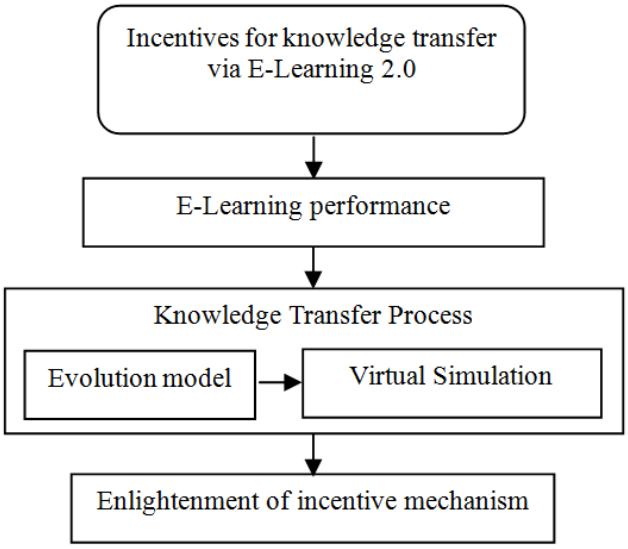

FIGURE 1. Research framework

Firstly, it is assumed that knowledge transfer via E-Learning 2.0 is stimulated by incentives. Secondly, E-Learners have unique knowledge attributes in terms of knowledge transfer capacity and knowledge state, and their goal is to maximize their total amount of reward received over the long run. Thirdly, the knowledge evolution model specifies how the learner changes his/her knowledge transfer policy as a result of interaction and collaborative learning. Fourthly, feedback from the simulation of knowledge evolution can shed light onto the incentive mechanism. Thereby, the optimal incentives for knowledge transferring that are derived in this article are suitable for E-Learners with different knowledge characteristics.

3.1. **Incentives for knowledge transfer via E-Learning 2.0.** Incentives give rise to rewards [26]. In the current case, rewards are special numerical values that the learner attempts to maximize for knowledge transfer via E-Learning 2.0 over time. The E-Learner can be named as the agent. The agent continually interacts with the changing knowledge environment by selecting proper knowledge transfer actions. Consequently, the knowledge transfer problem is a straightforward framing of the learning problem from interaction to achievement of a goal.

The agent interacts with the E-Learning 2.0 environment at each of a sequence of discrete time steps, $t = 0, 1, 2, 3, \ldots$. At each time step t, the agent receives some representation of the environment's incentives $i_t \in I$, where I is the set of incentives for knowledge transferring. On this basis, the agent selects an action, $a_t \in A(i_t)$, where $A(i_t)$ is the set of absorbing knowledge or assimilating knowledge in incentive i_t. One time step later, in part as a consequence of its action, the agent updates to a new performance state, $s_{t+1} \in S$, where S is the set of performance measures. If an agent can obtain greater or equal performance under an incentive policy i than under i', then the policy i must be as good as, or better than i'. There is always at least one policy that is better than or equal to all other policies. For the incentive-action pair (i, a), the optimal action-value function gives the expected return for taking action a under incentive i and thereafter following an optimal incentive policy. We test for three different types of incentive policy, one scenario is characterized by the low incentive policy, the second scenario is characterized by the middle incentive policy, and the third scenario is characterized by the high incentive policy. The incentives are randomly generated from the set of incentives $I(t) = RAND[0, 1]$ for knowledge transferring. Consequently, we divide our proposed incentives at time t into the following three levels: $I(t) = RAND[0.8, 1]$ (high incentives), $I(t) = RAND[0.4, 0.7]$ (medium incentives) and $I(t) = RAND[0, 0.3]$ (low incentives).

3.2. **E-Learning performance.** The current study analyzes the E-Learning performance measures of knowledge transfer network, knowledge transfer capability, knowledge inventory and knowledge value.

3.2.1. *Knowledge transfer network.* E-Learning 2.0 supports interactivity, interdisciplinary and social interaction by the online social networking. Online social networking supports the emotional and professional relationships of human beings or between their groups of mutual interests. The network is responsible for aggregating people with common interests. Thus, knowledge transfer network via E-Learning 2.0 has become an important way for people who have common interests, objectives and values to share ideas. Reagans and McEvily (2003) operationalized the ability to maintain diverse knowledge transfer relationships as network range [17], controlling for unobserved individual differences and the amount of knowledge overlap between the source and recipient, and they found that network range has a positive effect on the ease of knowledge transfer.

3.2.2. *Knowledge transfer capability.* Substantial barriers to knowledge transfer create difficulties and complications in transferring knowledge across networks. Members of knowledge transfer networks via E-Learning 2.0 not only absorb knowledge, they also simultaneously create new knowledge. However, if knowledge holders do not have sufficient ability to transfer the needed knowledge to recipients, the efficiency and effectiveness of knowledge transfer are greatly reduced. Meanwhile, if knowledge senders lack the appropriate ability, then knowledge transfer is marked by different interpretations of the same idea, false starts and disruptions [25]. Thus, it is reasonable to believe that efficient and effective knowledge transfer must consider both absorptive capacity and disseminative capacity.

3.2.3. *Knowledge inventory.* Knowledge inventory defines the stock distribution of different types of knowledge set among E-Learners at a particular time. An organization's stock of knowledge inventory is critical to the long-term development of a flexible knowledge-based workforce to meet future demand. Organizations can attempt to externally purchase needed talents from a spot labor market. However, much of the knowledge and skills are specific and often take time to learn. More importantly, knowledge inventory allows organizations to evaluate and address "skills gaps" and identify corresponding training strategies to assist in effective knowledge transfer [2]. The need to integrate knowledge transfer strategies with the operational aspects of business is a recurring theme in investigations of organizational incentives in knowledge creation [9].

3.2.4. *Knowledge value.* Knowledge life cycle determines the stochastic demand pattern of a particular knowledge or skill in the market over time [2]. Knowledge value is primarily based on its diffusion rate and the corresponding demand uncertainties of the knowledge [24]. The diffusion rate defines the rise and decay of the demand level for a given knowledge, whereas uncertainty in the demand for that knowledge defines the stochastic nature of the demands for the knowledge. When knowledge life cycles are short and volatile, E-Learners must be able to meet the challenge of the ever-changing market demands of new knowledge. Conversely, in an environment where knowledge life cycles are relatively long and stable, E-Learners have opportunities to prepare for and excel in a specific subset of strategic knowledge. In the present study, we conjecture that the knowledge transfer rate affects the knowledge value.

3.3. **Knowledge evolution model.**

3.3.1. *Virtual simulation.* To empirically explore knowledge transfer processes, researchers must observe the phenomenon over long periods of time. However, it is difficult to observe actual knowledge transfer, because it is an implicit process, especially the transfer of tacit knowledge. The behaviors that evolve from the interaction of groups, individuals and teams are complex, dynamic, adaptive and non-linear. Consequently, empirical studies are unable to accurately collect primary data on the evolution of network organizations [10]. Virtual simulation can provide unique perspectives on how individuals respond and how emergent patterns appear, taking into account uncertainty and ambiguity. Thus, virtual simulation is a useful tool in exploring knowledge transfer dynamics [16].

In our study of the interactions between various aspects of incentives for knowledge transfer network across E-Learning 2.0, the computational approach enables us to model scenarios that reflect the real-world phenomenon without restrictive assumptions [8]. First, in the current model, incentives drive the evolution of knowledge transfer network and network topology is a time varying, undirected graph. The knowledge demand of the E-Learner is stochastic. Additionally, E-Learners do not have complete information on other individuals' knowledge capabilities. Second, we relax the assumption of a random distribution for the knowledge transfer capacity of E-Learners. Third, we integrate the incentives decision with the long-term orientation of knowledge transfer and explore how changes in the knowledge transfer capacity affect knowledge inventory, knowledge value, and knowledge transfer network.

3.3.2. *Modeling knowledge network.* Consider that E-Learners exist in an undirected, connected network $G(V, E)$, where $V = (v_1, v_2, \ldots, v_n)$ is the node set and $E \subseteq V \times V$ is the edge set; elements in V can be called node or vertex, and elements in E can be called edge with corresponding (v_i, v_j) to each edge e_{ij} [18]. Through a simulated network based on this specification, we can investigate the dynamics of knowledge transfer via changing neighbor nodes and ties among nodes. The network parameters mainly include the numbers of nodes, node ties, each node's neighbor nodes and rules of nodes.

In the current paper, we treat the E-Learner as a node of the network. Links between nodes represent the channel of knowledge transfer. In reality, the knowledge transfer patterns conform to sets of interaction rules. Thus, we design two sets of rules to simulate behavioral patterns in the knowledge transfer process. One set is the rules of behavioral change and knowledge state change of nodes, and the other set is the interaction rules of nodes in the knowledge transfer network. The nodes are linked by the edges of communication. Moreover, the average links (ties) of each node are dynamic. The simulation of knowledge transfer is run on the scale-free network [12]. The scale-free network is generated according to the BA's algorithm: (1) Growth: starting with a small number (m) of nodes, at every time step, we add a new node with $e(< m)$ edges that link the new node to e different nodes present in the system. (2) Preferential attachment: when choosing the nodes to which the new node connects, we assume that the probability P_i that a new node will be connected to node i depends on the degree of d_i node i, such that $P_i = \frac{d_i}{\sum\limits_j d_j}$. After t time steps this procedure results in a scale-free network with $t+m$ nodes and $e*t$ edges, for which average degree is approximately $2*e$.

Moreover, research on three-node sub graph and four-node subgraph may aid in understanding the characteristics of knowledge interaction pattern through network structure. The appearance frequency and evolution tendency of the subgraph are then defined as $Z-score = \frac{N_{real}-N_{rand}}{std(N_{rand})}$, where N_{real} shows appearance times of certain sub graph in the target network, N_{rand} is the average times of certain sub graph appearance in a group of random network, and $std(N_{rand})$ reflects the standard deviation of certain sub graph appearance in the random network [19].

3.3.3. *Knowledge interaction rules.* This section presents the interaction rules of node members in knowledge transfer networks and reflects how node members interact with each other. Knowledge transfer is assumed to be proportional to the difference in knowledge inventory between broadcaster and recipient. When a broadcast takes place by i with disseminative capability β_i, the recipient j with absorptive capability α_j absorbs part of the knowledge that is transferred according to

$$KS_j(t+1) = \begin{cases} KS_j(t) & \beta_i * I_i(t) * KS_i(t+1) \le KS_j(t) \\ KS_j(t) + \alpha_j * I_j(t) * [\beta_i * I_i(t) & \text{otherwise} \\ *KS_i(t+1) - KS_j(t)] & \end{cases} \tag{1}$$

The value of α_j and β_i is provided by $\alpha_j = RAND[0,1]$ and $\beta_i = RAND[0,1]$, representing the random capacity of each node to absorb the new knowledge and to express and communicate its current knowledge to others respectively.

The value of $I_j(t)$ and $I_i(t)$ is provided by $1 + I(t) * RAND[0,1]$, denoting each node's random willingness to absorb and to disseminate knowledge respectively, due to incentives. The following three levels of incentive strategy are used: (i) $I(t) = RAND[0.8,1]$ (high incentive level) (ii) $I(t) = RAND[0.4,0.7]$ (medium incentive level) and (iii) $I(t) = RAND[0,0.3]$ (low incentive level).

Of note, the knowledge inventory is a measure of the amount of knowledge. The knowledge value of one agent i at time $t+1$ is modeled as a random diffusion process, where $\rho = \frac{KS_i(t+1)-KS_i(t)}{KS_i(t)}$. The value of ρ reflects the update rate of knowledge inventory for agent i at time $t+1$. The stochastic diffusion process of knowledge value is represented by the following equation:

$$KV_i(t+1) = KV_i(t)e^{-[1-\rho]} + \rho \tag{2}$$

The following two levels of knowledge transfer capability are used: (i) $\alpha_j = RAND[0.5,1]$ (high absorb) and $\beta_i = RAND[0.5,1]$ (high disseminate) and (ii) $\alpha_j = RAND[0,0.4]$ (low absorb) and $\beta_i = RAND[0, 0.4]$ (low disseminate). Thus, the experiment is a $2 \times 2 \times 3$ design (see Table 1), with two levels in each of the two factors (absorptive capability and disseminative capability) and three levels of incentives (low, mid, and high). The current study includes a total of 12 distinct experiments. Each experiment consists of 100 iterations [2], and each iteration simulates the organization for 1,000 periods. Each period can be considered to represent a time unit (most appropriately, a month).

Table 1. Regimes in the computational experiment

Regimes		Absorptive capability	
		High	Low
Disseminative capability	High	Regime 1	Regime 3
	Low	Regime 2	Regime 4

The timeline of high-level simulation steps is outlined as follows. At the beginning of the period, incentives encourage E-Learners to select the specific type of knowledge to communicate with others for collaborative learning via E-Learning 2.0. As a result, the corresponding knowledge state of each E-Learner may be updated, including linkage nodes, knowledge inventory and knowledge value. With the repeated process, we took several steps to address issues of external validity. First, parameter value ranges and probability distributions were selected based on guidelines from existing literature when available [4]. Second, in instances in which definitive guidelines were not available, practitioner and academic literature from related areas were utilized. Third, we connected the findings to those of studies on leading firms in knowledge-based industries to indicate that the essential aspects of the current model and findings resonate well with knowledge management practices and experiences in the real world.

4. **Results.** Summaries of results from the simulation experiments are presented in Tables 2-5. In these tables, the superscripts H, M, and L indicate that the specific incentive strategy is statistically greater than those identified by the corresponding superscript letters: H – High, M – Medium, and L – Low. The mean organizational knowledge inventory update related to different training incentives across different experiment regimes is provided in Table 2. Table 3 shows the mean knowledge value. Similarly, summaries of corresponding three-node sub graph and four-node sub graph related to different incentives levels and across different experiment regimes are presented in Tables 4 and 5 respectively. All values were first averaged over all 1,000 periods in an iteration and then over the 100 iterations prior to statistical testing. Each table shows four different regimes (Table 1) with combinations of high and low knowledge absorptive capability and disseminative capability.

Table 2. Knowledge inventory update by experiment and incentives strategy

Analysis variable: knowledge inventory update								
Experiment	*High Absorb, High Disseminate*		*High Absorb, Low Disseminate*		*Low Absorb, High Disseminate*		*Low Absorb, Low Disseminate*	
Strategy	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
High	$0.79^{M,L}$	*0.70*	$0.59^{M,L}$	*0.49*	$0.58^{M,L}$	*0.38*	*0.23*	*0.13*
Medium	*0.59*	*0.65*	*0.51*	*0.32*	*0.54*	*0.36*	$0.38^{H,L}$	*0.27*
Low	*0.48*	*0.60*	*0.48*	*0.31*	*0.39*	*0.29*	*0.23*	*0.17*

TABLE 3. Knowledge value update by experiment and incentives strategy

Analysis variable: knowledge value								
Experiment	*High Absorb, High Disseminate*		*High Absorb, Low Disseminate*		*Low Absorb, High Disseminate*		*Low Absorb, Low Disseminate*	
Strategy	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
High	$1.96^{M,L}$	0.37	$1.84^{M,L}$	0.37	$1.53^{M,L}$	0.18	1.42	0.63
Medium	0.92	0.96	0.75	0.29	1.05	0.47	$1.98^{M,L}$	1.47
Low	0.63	0.28	0.36	0.24	0.67	0.46	0.64	0.47

TABLE 4. Three-node sub graph update by experiment and incentives strategy

Analysis variable: occurrence of three-node sub graph								
Experiment	*High Absorb, High Disseminate*		*High Absorb, Low Disseminate*		*Low Absorb, High Disseminate*		*Low Absorb, Low Disseminate*	
Strategy	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
High	$497.4^{M,L}$	289.1	$486.8^{M,L}$	160.7	224.5	165.9	245.9	125.8
Medium	456.9	300	456.5	168.3	$282.8^{H,L}$	160.7	$289.4^{H,L}$	123.5
Low	432.6	301.3	406.1	197.1	174.9	157.5	218.6	128.9

TABLE 5. Four-node sub graph update by experiment and incentives strategy

Analysis variable: occurrence of four-node sub graph								
Experiment	*High Absorb, High Disseminate*		*High Absorb, Low Disseminate*		*Low Absorb, High Disseminate*		*Low Absorb, Low Disseminate*	
Strategy	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*	*Mean*	*Std. Dev.*
High	$656.8^{M,L}$	123.0	$610.5^{M,L}$	157.4	574.1	162.2	525.5	136.6
Medium	576.4	103.1	562.0	175.3	$622.6^{H,L}$	174.1	$586.3^{H,L}$	133.2
Low	497.0	102.8	543.6	151.1	523.2	160.6	528.4	135.8

In general, the building of knowledge inventory is highly dependent on the absorption and dissemination capability of knowledge. Table 3 indicates that the high-level incentive strategy results in higher knowledge inventory update across three experimental regimes. However, low absorption combined with low dissemination can create more knowledge inventory update as a result of a medium-level incentive strategy. Meanwhile, a low-level incentive strategy yields low knowledge inventory update across different experimental regimes.

Table 3 presents the knowledge value across different absorption and dissemination capabilities of knowledge. In general, with the same knowledge dissemination, the mean knowledge value is much higher in the better knowledge absorption situation. This result implies that absorption capability helps an organization to acquire more valuable knowledge for a competitive advantage. The results from Table 3 also suggest that dissemination capability plays a positive role in the value of knowledge; that is, a higher dissemination capability allows the transfer of a greater knowledge value (Column 1 vs. 2 and Column 3 vs. 4 in Table 3). Similar to the incentive strategy of Table 2, the high-level incentive strategy results in higher knowledge value across different experimental regimes except the low absorption combined with low dissemination regime. Furthermore, the medium-level incentive strategy works well on knowledge value under this regime.

Tables 4 and 5 reveal that, in most cases, a higher three-node sub graph occurrence corresponds with a higher four-node sub graph. Overall, high incentive strategy, which greatly awards E-Learners for acquiring the most updated knowledge available in the market, is much more desirable for high absorption E-Learners. By contrast, medium incentive strategy is more useful for low absorption E-Learners. When compared with Tables 2 and 3, there is little association between knowledge inventory level or knowledge value.

5. Discussions, Implications and Conclusions.

5.1. **Discussions and implications.** Overall, the findings indicate that a high incentive strategy provides better knowledge inventory update to the firm over the long run. Additionally, high absorption can facilitate better knowledge value and knowledge transfer.

High incentive strategy is relatively more beneficial to the occurrence of both three-node sub-graph and four-node sub-graph. Given that high absorption capability has an increasing trajectory of knowledge demand and knowledge values, high incentive strategy explicitly plays a catch-up game. It encourages E-Learners to acquire proficiency in the knowledge dimension and, thus, allows quicker adaptation to the knowledge dimensions available. The current results (Tables 4 and 5) reveal that high incentive strategy returns better collaboration in three-node sub graph and four-node subgraph in high absorption scenarios. When E-Learners pursue new knowledge in an E-Learning community, they would enjoy a high incentive strategy over the entire life cycle. More importantly, this high incentive strategy also produces a desirable outcome for organizations, i.e., rapid changes in knowledge.

High incentive strategy dominates medium incentive strategy. Medium incentive strategy is only beneficial when knowledge capabilities of both absorption and dissemination are low, which can be explained as high incentive strategy has less meaning in this situation. Thus, a medium incentive strategy may be suitable for specific conditions when E-Learning is in the initial stage to build an overall balanced knowledge portfolio. However, a low incentive strategy may not be beneficial to knowledge sharing. Therefore, organizations must promote or motivate E-Learners to participate even when high strategy does not explicitly outperform value [23].

Higher knowledge absorption capability improves knowledge value. Furthermore, higher dissemination builds the knowledge inventory. A plausible explanation for value improvement is that transfer capability facilitates knowledge application [11]. Knowledge inventory is valuable only if it is fully utilized and aligned with market demand [22]. Training more workers without proper alignment with the external environment is counterproductive.

5.2. **Conclusions.** E-Learning is a well-designed training strategy of knowledge management programs, in which knowledgeable employees are assigned to transfer specific knowledge that is important to the organization. It is becoming increasingly clear that updating employee skills and knowledge increases organizational flexibility and creativity.

E-Learning is critical for employees to acquire knowledge in business practices. However, selecting appropriate strategies that facilitate continuous participation in a dynamic environment is a complex problem that requires careful analysis. The current research addresses this problem by developing a model for knowledge transfer via E-Learning in a dynamic knowledge environment consisting of distinct knowledge transfer capability and knowledge characteristics. We investigated the impact of specific interactions between incentive strategies and the knowledge transfer capability on long-term knowledge transfer performance.

The results provide key insights into managing knowledge transfer. Overall, the findings shed light onto two important aspects of concern in knowledge transfer decisions:

choice of incentive strategy and effectiveness of incentive strategies in different knowledge environments.

These findings provide a framework and a context for further investigations of the impact of interactions between E-Learners and management strategies in E-Learning communities. To identify how E-Learning benefits the organization, profit calculations should be conducted in future studies.

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