BCOMP DISSERTATION

Looking Forward and Backward

The Significance of Cognitive Search in IS Development Process

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Looking Forward and Backward: The Significance of Cognitive Search in IS Development Process

H175060

WANG Xinqi (A0077988Y)

Abstract

Information System Development (ISD) project failure due to overwhelming complexity has been one intricate problem that confuses IS professionals for year without appropriate solutions. In this study, computer simulation was used to examine whether cognition, an approach that is proposed to deal with complexity in the literature of strategic decision making, would be effectively applied to ISD context and thus improve ISD performance. In this experiment, *NK* model was used to simulate the ISD process and cognition was modelled as a simple, low-dimensional representation of a more complicated, high-dimensional fitness landscape. Results show that, in spite of imperfectness, this simplified cognitive representation serves as a powerful start for subsequent experimental search. Therefore cognition is proved to be able to improve ISD performance. Nevertheless, it was also experimentally proved that cognition will improve performance only when project complexity is low to moderate. In addition, the choice of degree of such simplification by project managers will also impact the performance gain due to adoption of cognition.

Keywords: Cognitive search, Information System Development (ISD), *NK* model, project complexity, degree of simplification

1. Introduction

Although the exact number of failed Information System development (ISD) project is unknown, and the ways in which IS professionals perceive and define ISD failure may differ; the majority of large-scale ISD are considered unsuccessful (Goldfinch, 2007). According to a report published by the Standish Group in 2001, overall the success rate for ISD project was only 26% for all IS projects surveyed, with problems ranging from being over budget, behind schedule, to being delivered with less functionality than initially planned. Moreover, 28% were total failures or were even cancelled (Qassim, 2007). Although some researchers argue that such figures are overstated; the mainstream perception is still that failure has become the norm rather than the exception (Mahaney & Lederer, 1999). The inability to deal with overwhelming complexity has been cited as the major contributor to such failure (Qassim, 2007).

The fact that such problems have endured for three decades prompts us to consider whether solutions to or approaches for dealing with complexity proposed from distant disciplines may also be effective in solving the complexity problems inherent in ISD. In this study, we look to the strategic decision making literature to investigate whether an approach for dealing with complexity proposed there may effectively be applied in the ISD context. In the management literature, the impact of cognition on subsequent experiential learning is formally explored by Gavetti and Levinthal (Gavetti & Levinthal, 2000), and it is found that cognitive learning, allowing a broader examination of complex situations, will aid the conventional experiential learning process and thus improve overall performance of organizations that are seeking right strategic alignment for best performance (Gavetti & Levinthal, 2000). The fact that cognitive learning is a critical determinant of managerial choice and action also further confirms the significance of cognitive learning in real life situations (Walsh, 1995). Therefore with respect to the extremely low success rate which has tortured IS professionals for several decades with no apparent solutions (Goldfinch, 2007), such findings suggest value in examining cognitive search as a potential means to improve the performance of problem-solving processes such as ISD.

When viewed from the perspective of organizational problem solving, a number of practices prevalent in ISD do seem to be related to the notion of cognitive learning. For example, in Scrum, a popular ISD methodology (ISDM) used in practice, artefacts such as Product and Sprint Backlogs, which are essentially lists of requirements containing rough (i.e., simplified) estimates of both business value and development effort, aid in understanding and discovering of important and valuable system features just as cognitive learning does in identifying potential "high performance" areas in managerial decision making. In spite of the prevalence of such practice, *whether* cognitive search in ISD can actually help improve ISD performance, *under what condition* it can help or *how* exactly its contributions unfold with respect to different types of ISD projects has yet to be rigorously scrutinized . With respect to Waterfall approaches, there is currently no practice associated with cognitive search. Therefore whether cognitive search will have different contribution to the performance of ISD projects with Waterfall is also of interest to be uncovered.

In order to unravel the myths and answer the above questions which have not been addressed in previous literature, this study aims to discover the role of cognitive search in the ISD process, specifically how it will help with respect to one of the most the prevalent ISD methodologies, namely Waterfall Methodology. In this study, computational modeling using simulations is used to theoretically explore the role of cognitive search in ISD processes to develop theoretical propositions, which may serve as the basis for future empirical research. The reason that a simulation approach is adopted in this paper mainly lies in the fact that simulation is an effective tool for developing theory from simple assumptions (Axelrod, 2003). Moreover, unlike field study in which it is relatively difficult to systematically manipulate variables of interest, simulation researchers can freely adjust parameters to gain insight through combining different experimental conditions. In addition, simulation enables to rigorously model phenomenon without resorting to simplifying assumptions for analytical tractability. Therefore considering all these benefits, simulation is used as the research approach.

2. Theoretical Background

2.1 ISD As a Problem Solving Process

Since ISD can be regarded as an information collection, processing and feedback process, it can be conceptualized as search within a configuration space (Newell & Simon, 1972)– i.e., a problem solving process where the team tries to identify (or "search for") a system configuration which can deliver the most value to the organization. This process is generally iterative and incremental in current ISDMs, and therefore it can be structured as an iterative search process: Waterfall Methodology, a "plan-based" ISDM, can be conceptualized as searching with the scope of the full system from the beginning to the end.

During the search (i.e. system requirement analysis and design), teams are faced with many difficulties, a typical one of which is the significant amount of interdependencies among those decision factors the teams try to configure. The existence of interdependencies largely increases ISD project complexity, which in turn reduces the likelihood of reaching the optimal ISD configuration which produces maximal performance. In this sense, a mechanism which can simplify such complexity will effectively address the difficulty. Cognitive learning, representing one example of this mechanism, has been partly adopted in some ISD practices such as the retaining of a "Product Backlog" during system design phase to improve ISD performance. The details of what cognition is and how this cognition helps in the context of ISD will be discussed more in the following section.

2.2 Cognitive & Experiential Search

There are two different but interrelated approaches to intellectual action: one is "cognitive learning", the other is "experiential learning". Cognition usually refers to an information processing view of an individual's psychological functions (Sternberg, 2009). Due to bounded rationality, actors often use an imperfect representation to form mental models of their environment (Thagard, 2005). However, in spite of imperfectness, such cognition still helps simplify the complexity of spatial relationships, temporal relationships, and causal relationships, and therefore will ease the decision making process by helping to quickly identify the fruitful initial directions (Porac, Thomas, Wilson, Paton, & Kanfer, 1995). In contrast, experiential wisdom accumulates as a result of positive or negative change of prior choice: those choices resulting in better outcomes will be reinforced, while those resulting in worse will be discarded (Levitt & March, 1988). Both Cognitive Learning and Experiential Learning are processes of transforming information into action and knowledge, and the relationship between these two distinctive methods is shown in Figure 1 below.

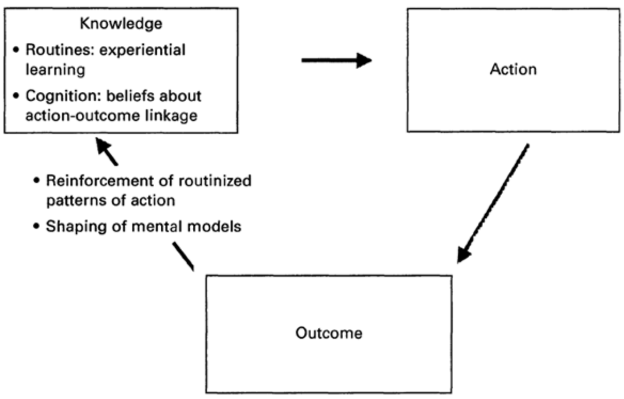


Figure 1. Intelligence of Action (adapted from Gavetti & Levinthal (2000))

Experiential learning is essentially a "backward-looking" process of "local search", meaning the search is over the alternatives in the neighbourhood of current situation. However, such search mechanism is subjected to inherent weakness of myopia: small changes may lead to inferior performance while substantial changes may potentially identify a superior solution (Gavetti & Levinthal, 2000). This weakness can be addressed when "forward-looking" cognitive search complements experiential learning. This is because cognitive search looks at the problem from a broader perspective, and thus can help quickly identify the correct direction where the optimal solution lies. Therefore in a complex environment, the combination of cognitive and experiential search will generally lead to better performance in that crude cognitive representation provides a powerful starting point for subsequent experiential learning effort (Gavetti & Levinthal, 2000).

2.2.1 Cognitive and Experiential Search in the Context of ISD

In the context of ISD, Cognitive Representation refers to the perceived design and structure of the system to be delivered, which is usually a simplified representation of the actual system structure. For example, the major artefacts in Scrum are Product and Sprint Backlogs which essentially are ordered lists of "requirements" that are maintained either for the whole product (i.e., Product Backlog) or for a single round of iteration (i.e., Sprint Backlog). Such backlogs consist of what needs to be completed to successfully deliver a working software system, ordered based on priority factors such as risk, business value, dependencies, and deadline. The backlog serves as a rough estimate of both business values and development effort perceived by the team, and therefore it is considered as a simplified cognitive representation. Such cognition help gauge the timeline and prioritize the requirements instead of thoroughly defining the problem all at once, thus in turn help improve ISD performance. In contrast, experiential search in the context of ISD refers to the process of "trial-and-error" or "prototyping". This means the ISD team will do some implementation first, and then subsequently get actual feedback for the alternative implemented (Lippman & McCall, 1976). Experiential search helps in ISD performance improvement in that it exploits both the current wisdom associated with existing actions and takes up the opportunity to engage in some degree of search and experimentation for superior alternatives (Gavetti & Levinthal, 2000). Even though there are some industry practices that seem to support that both cognitive search and experiential learning can help deal with complexity and subsequently improve ISD performance, such argument has not been formally examined and experimentally proved.

2.3 Research & Hypotheses

As previously confirmed in the context of organizational behaviour, the adoption of cognitive search can improve organization performance (Gavetti & Levinthal, 2000). Thus it is also expected that cognitive search can aid ISD team to gain better performance:

> *Hypothesis 1*: *Cognitive search (Forward Looking Process) will help project team perform better in the IS development process*

In the study conducted by Gavetti and Levinthal, the reason that cognitive search positively contribute to better performance is because cognitive search can help agent identify potentially more favourable directions as a starting for subsequent experiential search (Gavetti & Levinthal, 2000). However, such perceived 'simple map' may be only meaningful in guiding the agent's search direction when such map can well capture the characteristics of the real landscape. Obviously, it is easier to retain the characteristics of real landscape when the environment complexity is low, therefore it is expected that Cognitive Search will improve performance more significantly when the environment complexity is low.

> *Hypothesis 2: The advantage of Cognitive Search will be more prominent in an environment with low to moderate complexity.*

In terms of agent's degree of simplification, the resulting gain should be the most significant when such simplification is moderate. Either under-simplification or over-simplification will lead to a situation where agents search in a perceived landscape which may not well represent the actual landscape. Thus it is proposed that the advantage of Cognitive Search will be more meaningful when the degree of simplification is moderate.

Hypothesis 3: The advantage of Cognitive Search will be more prominent when the degree of simplification is moderate.

To examine the three hypotheses proposed above, we develop a computational model of ISD that will be systematically explored using simulations. The modelling details are illustrated in the section below.

3 Model

The *NK* fitness landscape model, as a commonly used simulation approach for studying complex adaptive system when the phenomenon of interest can be conceptualized as search based adaptation, is employed to study the influence of cognitive search on the ISD process and outcomes. As a computational model featured by the concept of a "tunably rugged" fitness landscape, the *NK* model is used to describe the way an agent may search a landscape by manipulating various characteristics of itself, just as an ISD team searches through different configurations and adjusts decisions accordingly to attain the satisfactory results. Here *N* stands for the overall size of the decision space , and it maps to the total number of decisions that need to be made in the ISD process; while *K* is the overall ruggedness, or the number of local "hills and valleys", and it maps to the degree of interdependencies of the ISD decisions.

3.1 The *NK* Fitness Landscape Model

The *NK* fitness landscapes model is an analytical framework for studying the statistical properties of complex adaptive systems (Kauffman, 1989). It is used to uncover in different environments the performance implications of agents with goal-oriented adaption behaviours, which is essentially configuration on decisions such that performance is maximized. An agent, representing an organization or a team, can be modelled as consisting of *N* distinctive decision factors, where each factor contributes to overall performance of the full configuration. There may be some level of interdependencies among these decision factors, the amount of which is represented by *K*: the higher the *K* is, the more interdependent the decisions are and thus more difficult for agents to navigate the performance landscape. The modelling framework enables researchers to generate stochastic fitness landscapes, on which computational agents with predetermined search strategy can be seeded and their behaviours observed. The reseachers can find the statistical properties of such adaption process by tuning landscapes with varying complexity *K* for a given number of decisions *N*.

3.1.1 Modelling Landscape

We model the ISD project as a consisting of *N* decisions, be it related to business requirement or system requirement. Each decision d_i can take the value of either 0 or 1, representing two fundamentally different choices. Therefore the overall IS configuration can be modelled as a vector with *N* elements or designing decisions: $\mathbf{d} =< d_1, d_2, d_3, \dots, d_n >$, and in total there are 2^N possible configurations. There is a fitness value for every configuration, and this value can be interpreted as the performance of the configuration if it is actually implemented.

3.1.2 Modelling the Agents Adaptation

Each agent represents an independent ISD project searching for the configuration that can bring about the best performance. Their search strategy is local hill-climbing to navigate around neighbourhood within the landscape for the greatest fitness value by adjusting their design choices. Here we assume that agents are boundedly rational: meaning that agents are unable to discover the underlying structure of the interdependencies, rather, they sample the currently available alternatives and evaluate their feasibility based on associated fitness values. More specifically, they can only evaluate the nearby one-off alternatives that are in the immediate neighbourhood around the current coniguration, rather than considering distant configuration which differ from the current configuration in more than one decision factor (Hahn & Lee, 2012). For example, in a landscape with *N*= 4, if an agent starts with the configuration of <0,0,0,0>, then the agent will consider four alternatives which are in the immediate neighbourhood around the current position, namely <0,0,0,*1*>, <0,0,*1*,0>,<0,*1*,0,0>,and <*1*,0,0,0>. The agent will evaluate the fitness value of the four alternatives and compare these with the fitness value associated with current position, and he will adopt the one with highest fitness value. In this example, suppose the agent selects <0,0,*1*,0> which has the highest fitness value, then subsequently he will evaluate among <0,0,1,*1*>, <0,*1*,1,0>, and <*1*,0,1,0> (<0,0,*0*,0> will not be considered as it has been evaluated to be inferior in the previous round). The agent will continue searching in this way until he reaches a point where any alternatives in the immediate vicinity are inferior, a situation commonly referred to as a “Sticking Point”. Such “Sticking Points” might not be the global peak, but rather a local peak which limits the agent effectiveness of local experiential search and thus leads agent to competency traps when local experiential search suggest this is the best solution while a global search might suggest a more superior solution (Gavetti & Levinthal, 2000).

With respect to decision making process, since each round the decision made is a *N*-element vector $\mathbf{d} =< d_1, \ldots, d_N >$, the contribution of each decision to the overall fitness F(**d**) of such decision **d** will be $c_i = c_i\left(d_i \middle| K\ other\ d_j's\right)$ with the consideration that there are K interdependencis between d_i and other decisions. Such interdependencies are illustrated in a

N-by-N Influence Matrix (**INF**), where INF_{ij} = 1 if (column) decision variable j influences the value contribution of (row) decision variable i, or 0 otherwise. The fitness value c_i is typically determined by a random drawing from a uniform distribution [0,1], and the overall fitness level of a particular decision **d** will be the average of all $c_i' s: F(d) = \frac{1}{N}\sum_{i=0}^{N} c_i$. This procedure allows the researcher to create stochastic landscapes with similar level of structural complexity given a particular value of *K*.

In each period(round), a randomly selected decision choice is flipped and the new fitness value is evaluated against the current value. The new configuration will only be adopted if such new value exceeds the current performance:

$$d_{(t+1)} = \begin{cases} d_{new}\ if\ F(d_{new} >\ d_t) \\ \quad d_t\ otherwise \end{cases}$$

Waterfall looks at the project from a full systems perspective, and will not "look back" once the previous design and configuration is fixed. Therefore in our model, the agent with Waterfall as the ISDM will be able to see all *N* decision factors from the beginning. In the process of searching for the best configuration, all N decision factors can be manipulated to attain the highest performance.

3.2 Modelling "Cognitive Learning" in *NK* Landscape

We are interested in using the *NK* fitness landscape to model not only processes of experiential learning but also actor's simplified cognitive representation of their decision context. It is assumed that cognitive representations are grounded on the actual landscape, but of lower dimentionality than it (Gavetti & Levinthal, 2000). It makes sense as in psychology cognition is essentially a simplified and imperfect abstraction of the real world situation, and it is also consistent with both academic literature and managerial practices such as the Boston Consulting Group Matrix (Hax & Majluf, 1984). Hence in our model, in order to capture this notion, the cognitive representation perceived by ISD project team consists of *N1* dimension, where *N1*< *N*. The mapping between such cognition and the actual landscape is intuitive: each point on the perceived landscape is assigned a fitness value that is the average fitness value of all combinations on the actual landscape that are consistent with this point: that is the average of 2^{N-N1} different values. Therefore the lower *N1* is, the less perception and sophistication capability the agent has, the more obscure such cognitive landscape is. After identifying the optimized configuration with respect to the *N1* factors, subsequently the agent will experiment using experiential search over the set of 2^{N-N1} choices consistent with the *N1* choices determined by cognitive representation.

The modelling of experiential search through the subsequent 2^{N-N1} combinations will be the same as prior research settings: it will be characterized as a process of local search, meaning only one element of the *N* dimensional array is varied at one time.

3.3 Modelling Cognitive Learning With Respect To ISDM

The modelling of cognitive learning is very straightforward: the *N1*factors perceived by agents will be randomly selected from the total *N* factors. Since *N1*<*N*, at first agent will optimize configuration by varying only these *N1* factors. Once an optimization has been reached, this design configuration is fixed and subsequently a local search representing experiential learning will be conducted within the remaining *(N-N1)* factors to find the best adaptive solution.

4 Experiment Design

4.1 Experiment 1: Explore The Role of Cognitive Search in ISD Process

The first experiment compares the impact of combined search method of both experiential learning and cognitive learning on ISD teams with Waterfall as development methodologys. It also serves as a base case for subsequent experiments with varying parameters (i.e. *N*, *K*, etc.) for comparison.

4.1.1 Experiment Design & Setting

There are two types of agents to be modelled in this experiment: each with different combination of search strategy, which are respectively 'Pure Experiential Learning' and 'Combined Cognitive & Experiential Search'. Those with "Pure Experiential Learning" will be labelled as 'Group 1', and the rest with 'Combined Cognitive & Experiential Search' will be labelled as 'Group 2'. The number of each type of agents is set to be 50, which is large enough to stabilize average performance reducing the impact of outliers.

For a single round, the number of periods allocated to each type agent is identically 30, Sufficiently large for agent to have enough time to search on the landscape and attain their own optimized performance; *N* is set relatively large (16) to let agents have enough space to search, and the landscape is set to be neutrally complex (*K*=6). A total number of 100 rounds will be conducted and the average performance of each type of agent will be used for final comparison.

4.1.1.1 Property Setting With Respect To Cognitive Search

For agents using both experiential and cognitive search as strategy (Group 2), the dimensionality *N1* of their perceived landscape is 12. This means that they will firstly search by configuring the 12 decision factors, then subsequently they will search by configuring the remaining 4 decision factors with the first 12 factors configuration unchanged.

For agents using pure experiential search as strategy (Group 1), they will search on the real landscape with *N* = 16 right at start. This is different from the latter group, who start searching on their perceived landscape first, then search within part of the actual landscape subsequently. Figure 2 summarizes the property settings of both type of agents

	Group 1	Group2
N	16	16
K	6	6
ISDM	Waterfall	Waterfall
Search Stategy	Pure Experiential	Combined Cognitive and Experiential Learning
N1	N.A	12
Time	30	30
#Agents	50	50

Figure 2 The property setting of each type of agent

4.1.2 Performance Measurement

To rectify the performance difference due to different landscape topologies, each performance record should be normalized to make inter-landscape comparison impartial. Within each group, the average performance attained in each round will be considered primarily.

Subsequently after 100 rounds of experiment have been conducted, the average performance over 100 rounds will be calculated and recorded. To verify the first hypothesis, the average performance over all agents belonging to Group 1 will be calculated as *P1*, and the average performance over all agents belonging to Group 2 will be calculated as *P2*. The conclusion will be reached and the first hypothesis will be verified if $P1 < P2$.

4.2 Experiment 2: Explore The Role of Cognitive Search in ISD Process With Varying Complexity

The objective of second experiment is to examine the above conclusions with different complexity K. It is expected that the less complex the environment is, the more advantages there will be when adopting cognitive learning in addition to traditional experiential learning. With respect to every set of experiment, we follow the uni-variate principle, which allows only one single variable changes at one time while keeps other variables unchanged. This is used to examine the impact of such single variable on overall performance, excluding all impacts of other factors rather than this single variable.

4.2.1 Experiment Design & Setting

Essentially the setting is the same as in the first experiment, but this time we will keep all other settings unchanged except for the complexity K. In the first experiment the environment is set to be neutrally complex with $K = 6$, hence here K is set to be from 1 to 15 to reflect different levels of complexity and examine the performance of each group of agents in the environment with such complexity.

4.2.2 Performance Measurement

To rectify the performance difference due to different landscape topologies, each performance record should be normalized to make inter-landscape comparison impartial. Within each group, the average performance attained in each round will be considered primarily. For each level of K, the average performance over all agents belonging to Group 1 will be calculated as $P1'$, and the average performance over all agents belonging to Group 2 will be calculated as $P2'$. The difference between these two average performances will be calculated as $D = P2' - P1'$. Next we will plot these performance differences D's against their respective complexity levels and apply regression techniques on them: if a positive correlation can be observed, the hypothesis “the more complex, the more advantageous there will be if adopting cognitive search” will be verified.

4.3 Experiment 3: Explore The Role of Cognitive Search in ISD Process With Varying Perception Capability

The objective of Third experiment is to examine the above conclusions with different simplification degree *N1*. It is expected that more advantages there will be when adopting cognitive learning in addition to traditional experiential learning when the degree of simplification is moderate.

4.3.1 Experiment Setting

Essentially the setting is the same as in the first experiment, but this time we will keep all other settings unchanged except for the agent’s degree of simplification *N1*. In the first experiment, *N1* is set as 12 out of 16 decisions in total. Therefore *N1* here is varied to be 1 to 15 for each complexity level *K* to reflect different levels of agent’s choice of simplification degree.

4.3.2 Performance Measurement

To rectify the performance difference due to different landscape topologies, each performance record should be normalized to make inter-landscape comparison impartial. Within each group, the average performance attained in each round will be considered primarily. For each level of *N1*, the average performance over all cognitive agents searching in equivalently complex landscape will be recorded as P. Subsequently we will plot P against *N1*to find the relationship between them: if a “bell curve” can be observed, the third hypothesis will be verified.

5. Result Analysis

5.1 The Impact of Cognitive Search in ISD Process

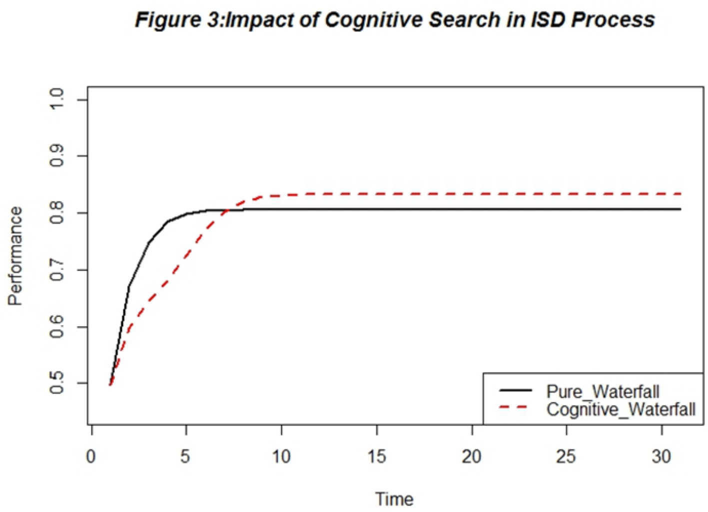


Figure 3: Impact of cognitive search in ISD process

Figure 3 shows how cognitive search can improve ISD performance for projects adopting Waterfall methodology when project complexity is moderate (K=6) and project size is medium (N=16). As discussed in the previous section, ISD performance is measured as the average of the highest performance attainable for each agent on each landscape. It clearly shows in Figure 4 that projects with cognitive search strategy outperform projects with pure experiential search strategy. However, in terms of the rate at which performance increases, pure waterfall projects improve their performances faster than cognitive waterfall projects. Nevertheless, cognitive waterfall projects finally reach better position ultimately, meaning ISD projects with cognitive strategy are able to reach a much higher performance than those with simply pure experiential search strategy.

5.2 The Impact of Cognitive Search in ISD Process with Varying Complexity

Figure 4:Performance of Pure Waterfall With Selected K

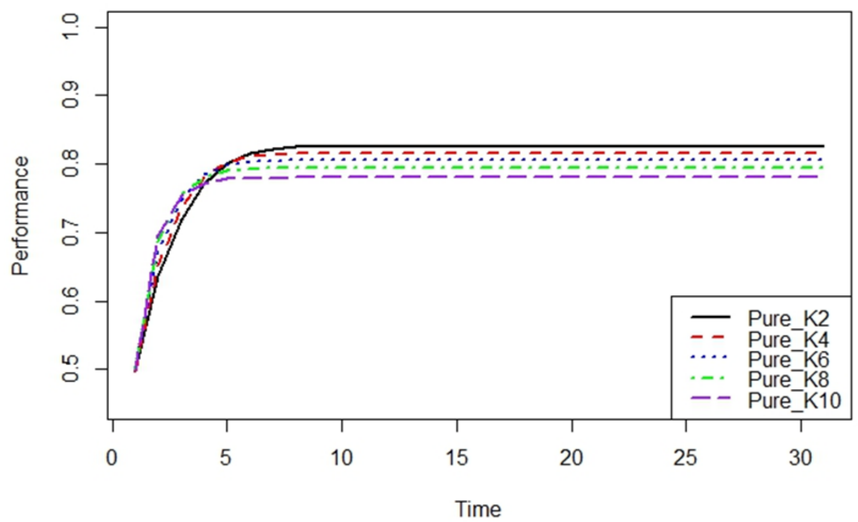


Figure 5:Performance of Cognitive Waterfall With Selected K

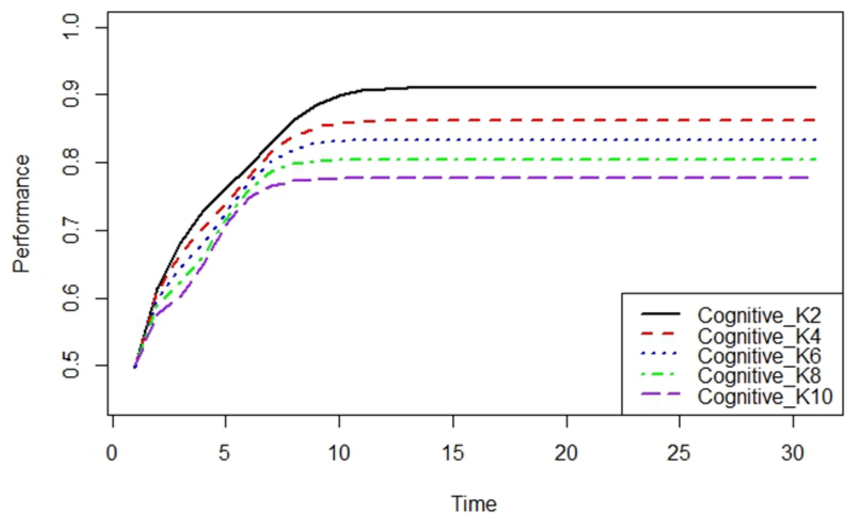


Figure 4&5: Impact of complexity on performance with respect to different search strategies

As shown from Figure 4 above, the performance of projects with cognitive search and waterfall will be worse with more complexity, and it is also the same with projects with pure experiential search strategy (Figure 5)[1]. Comparing the differences between performances of cognitive waterfall projects and pure experiential search waterfall projects, we have found that with the increase of complexity level K, such difference will narrow; when the landscape is highly complex (K>10), conversely projects with pure experiential search will outperform projects with cognitive search (Figure 6)

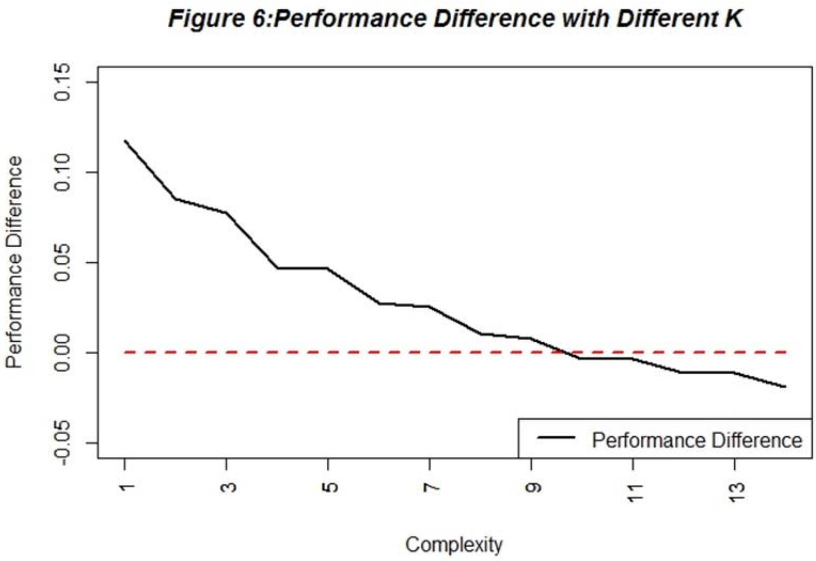


Figure 6: The performance difference between Cognitive Waterfall and Pure Waterfall with respect to different level of complexity

Even though cognitive representation can enhance the initial adaptive behaviour so that the attractive ‘peak area’ will be more easily discovered, such representation may not be able to effectively capture the characteristics of the actual landscape with higher level complexity, therefore the performance of cognitive search is inferior to that of pure experiential search. It is also discovered in this experiment that, when complexity increases, the downgrade of performance of cognitive waterfall will be more significant than that of pure experiential

[1] The simulation model was run with all values of K (1…15) for both combined cognitive search and pure experiential search. Figure 4 & 5 only show the situation when K = 2, 4, 6, 8, 10 for brevity.

waterfall. Experimentally this can also explain why at higher level of complexity, the performance difference will decrease or even become negative.

5.3 The Impact of Cognitive Search in ISD Process with Varying Degree of Simplification

Figure 7(a):Impact of Degree of Simplification on Performance(K Low)

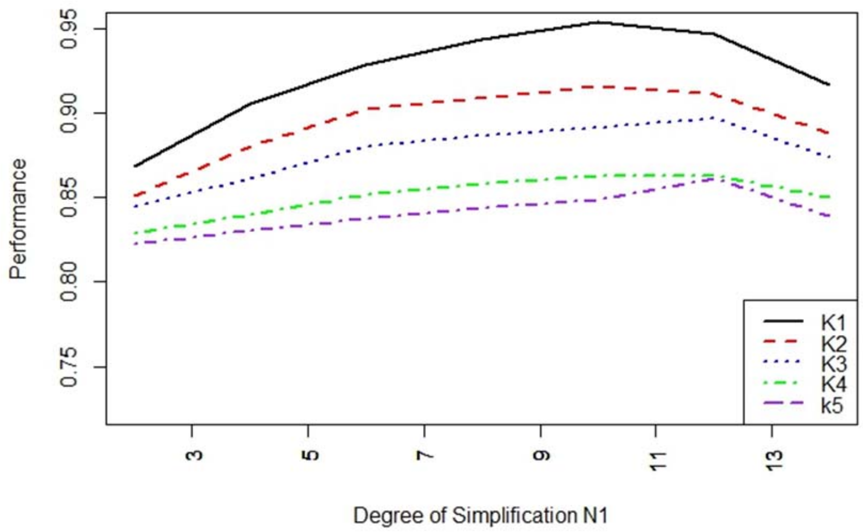
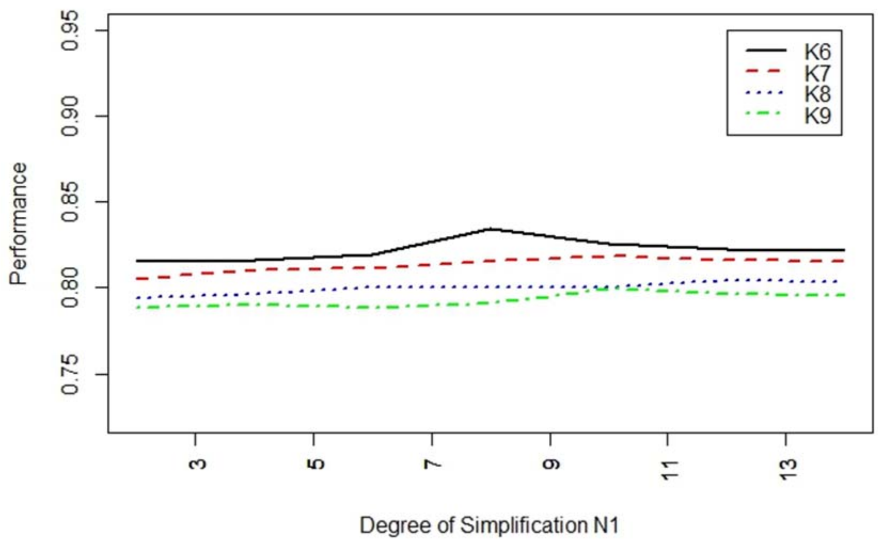


Figure 7(b):Impact of Degree of Simplification on Performance(K Moderate)



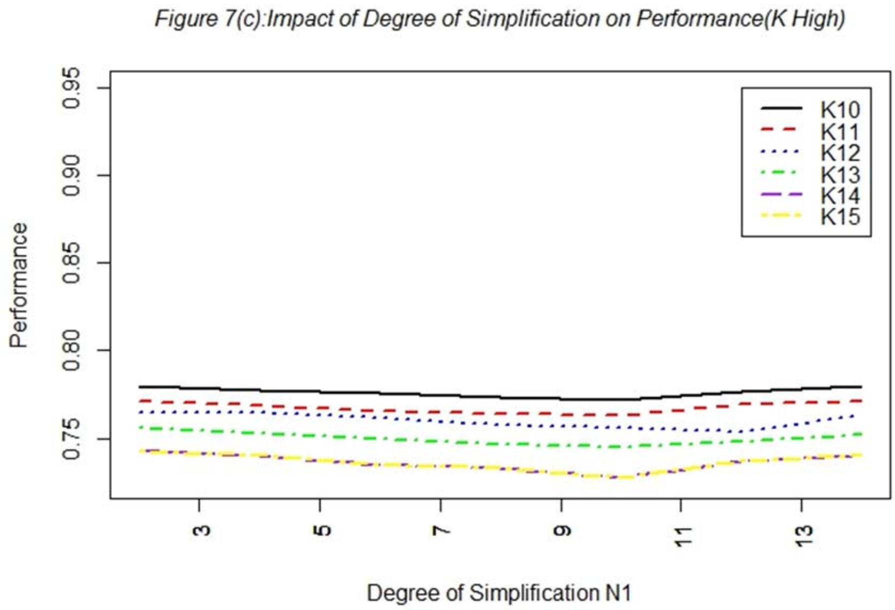


Figure 7:The impact of degree of simplification on the performance of ISD projects with Waterfall Methodology

From this experiment, there are three interesting discoveries to be noted. Firstly, as shown in Figure 7(a) above, the lines are generally inverted-U shaped, with peak located between N1=8 and N1=12. This indicates that, when the environment complexity is low to moderate (i.e. *K* <=5), a moderate degree of simplification (i.e. *N1* is between 8 to 12 out of total N 16) will help improve performance to the most extent. Secondly, as shown in Figure 7(b), the lines are all flat, with no obvious peaks or troughs. Therefore no obvious relationship between agent's choice of degree of simplification and performance improvement can be observed in the situation where environment complexity is moderate (i.e. *K* between 6 and 9). Thirdly, as shown in figure 7(c), a general u-shape can be clearly observed for all lines. This means that instead of improving performance, a moderate degree of simplification will conversely lead to more inferior performance than over-or-under simplification when the environment complexity is high. In this case, if using cognition, it suggests that either little simplification or a large extent of simplification should be adopted. This figure also indirectly proves the second hypothesis that cognition will downgrade performance in a complex environment. When putting the three graphs together, in terms of the line shape, there is an obvious trend that the curve changes from convex to concave with the increment of complexity. Therefore adoption of cognitive search will improve performance more significantly in the situation where there are not many interdependencies among decisions.

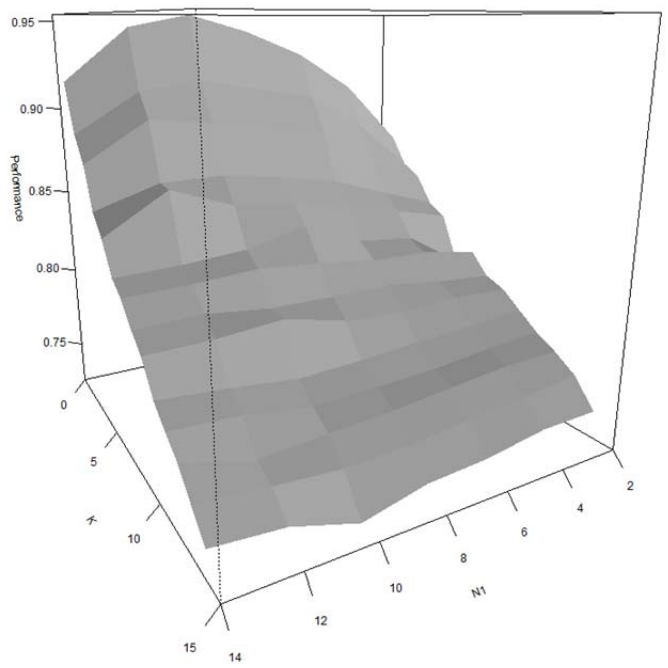


Figure 8: 3-D representation of the interrelationships between performances, complexity, and degree of simplification

With the experiment data from all three experiments, the interrelationship between performance, environment complexity, and degree of simplification can be depicted in a 3-D graph as shown in Figure 8. It can be observed that along y-axis (Labelled by ‘K’), performance generally goes down with higher level of complexity, regardless of choice of degree of simplification. While along x-axis, at lower level of complexity, the plane is convex-shaped with peak locating in middle area, meaning a moderate level of simplification will attain the best performance; nevertheless, when environment complexity is high, the plane shape changes to concave, indicating that the adoption of cognitive learning in addition to experiential learning will conversely downgrade performance, and among all the choices of simplification level, a moderate level simplification will lead to the worst performance.

6. Discussion and Conclusion

The two fundamentally different forms of intelligence, namely backward-looking experiential learning and forward-looking cognitive learning, are both important organizational behaviours. By focusing on the linkage between them and how cognitive search will improve the performance when combined with pure experiential search, specifically in the context of ISD, three sets of results have been derived.

Firstly, cognitive representation perceived by agents help improve the performance of ISD. It is meaningful because it constrains the process of experiential search from wandering into less attractive regions in the landscape(Gavetti & Levinthal, 2000). For experiential search, which is essentially a process of searching over the spaces of neighbourhood alternatives, it is inherently limited by landscape topography. For example, it may well be the case that an agent stops searching where all incremental changes lead to inferior performance while a more substantial change may locate a more favourable point in the landscape. This phenomenon is ‘competency trap’(Levitt & March, 1988) and it is one of the barriers that prevent experiential learning agents from reaching superior point. In the context of ISD, for example, such ‘competency trap’ can be the situation where a tiny configuration change cannot significantly improve the IS performance while only huge changes will do.

In contrast, cognitive search allow a much broader examination on the landscape. Even though the initial perceived representation may not be perfect, it does help with the identification of promising locations on the landscape, and directs a favourable area for subsequent experiential search. With respect to ISD process, the cognition is essentially a rough pre-analysis of the project and a prioritization of requirement. These initial efforts will greatly accelerate and ease the decision making process and thus expedite the subsequent development process and result in better delivery performance.

Secondly, with respect to project complexity, the performance improvement due to adopting cognition differs with varying complexity. As discovered, such performance improvement will be more significant when project complexity is lower. When the project complexity ranges from high to extremely high, conversely the practice of cognition will downgrade the overall ISD performance (Figure 6). In the context of ISD, the complicated interrelationship among decision factors will make beforehand estimation and prioritization extremely difficult. Therefore unlike in the situation where project complexity is low, such simplification may not well capture the characteristics of the actual project or the complicated interrelationships among decision factors. Consequently it is suggested that cognition should be adopted when project complexity is low, moderate or reasonably high.

Thirdly, with respect to agent's choice of degree of simplification, the performance improvement also differs. For projects with lower complexity, a moderate to low degree of simplification will improve performance most (Figure 7(a)). A high degree of simplification may simplify the interrelationship too much and thus such simplification may not well represent the actual project characteristic. In contrast, a very low degree of simplification forgoes the benefits of cognition, though it may well capture the characteristics of the actual project more thoroughly. In fact, a low degree simplification is almost equivalent to no simplification, thus the gain in performance is not notably significant. Ideally the performance gain will be the largest when the degree of simplification is 20~40%, meaning the number of decision factors included in the simplified representation should be 60~80% of total number of decision factors.

The implication of these three findings for industry practitioners is notably significant. To begin with, in the traditional ISD process Waterfall Methodology is still a popular choice for project managers due to it well-understood structure and easy management; however, as a linear-sequential life cycle model, Waterfall requires large amount of analysis at the beginning which is relatively time-consuming. It is usually the case that owing to time constraints and IT illiteracy of clients, the requirements are not understood thoroughly and therefore the design configuration is neither as expected nor performs well(Alam, 2012). In this situation, it is recommended to project managers that cognition should be considered as to reduce the problem size and the sets of alternatives to be evaluated. An alternative, characterized by the cognitive representation, may be a template, or an outline, or a rough estimation. From there as a starting point, project managers may subsequently experiment with different configurations which are consistent with the cognition, to find the most optimized solution.

However, project managers should pay special attention to the overall complexity of ISD projects. As suggested by the second experiment above, the adoption of cognition will notably improve the performance of IS when project complexity is low to moderate. With fewer interrelationships among decision factors, a cognitive representation such as a prioritized requirement list will effectively capture the essential characteristics of the project, simplify the decision making process, and aid in improving ISD performance consequently. Nevertheless, in the situation where project complexity is high, such form of cognitive representation will conversely downgrade the ISD performance. This is attributed to the imperfect abstraction of the original project properties for the cognitive representation. With such a misleading starting point, it may well be the case that an inferior ISD performance can be expected. Therefore it is of significant importance for project managers to analyse project scope and its complexity thoroughly before making the decision to adopt cognition.

With respect to those projects with cognition adopted as development strategy, project managers are also faced with question of which degree of simplification should be used. As concluded from our third experiment, when the project complexity is low to moderate, an optimal degree of simplification is 20% to 40% of the project size, meaning the selected decision factors by project managers to start from scratch should be totalled up to 60% to 80% of the number of all decision factors need to be considered. Regarding the selection process of these perceived decision factors, divergence may arise as a result of different views of the project. In fact, a critical element of expertise is the divergence in an expert’s representation of a problem space from that of a novice(Chi, J.Feltovich, & Glaser, 1981). Therefore project management experience is very important to project managers, in terms of not only the selection of initial decision factors for a start, but also the subsequent experimental search and configuration within the remaining decision factors.

In this research, the ISD process is conceptualized as a process of search within a design space using strategies of cognitive learning and experiential learning. Using *NK* Fitness Landscape to model this process enables us to explore the complex relationship between cognitive learning and ISD performance. The study extends the prior research on benefits of cognitive learning on organizational performance, to the background of ISD. The objective of this study is to drive a new theoretical insight about the influence of psychological factors on ISD performance, and the findings of this study will inspire further practical application of cognition on ISD process, thus in turn improve the ISD performance and success rate. Nevertheless, the benefits of cognition with respect to ISD are not fully revealed in this research. Although we have formally examined the positive impact of cognition on the performance of ISD with Waterfall Methodology, we did not test its influence on performance of projects with other ISDMs, such as Agile. Also, in real world IS development, it may be the case that the project scope is not clear or the project requirement changes from time to time. These factors are not reflected in the current model; therefore more needs to be done to characterize more accurately such ISD process in future research.

Appendix A: Model Robustness Test With Different Number of Runs And Different Number of Agents For Each Run

Here we rerun the simulation with more runs and larger number of agents for each type of agents, there was no significant variance observed. For brevity only robustness test result for the first experiment is shown in the table below, other robustness test results will be available at request

Cognitive Waterfall	100 runs/50 agents	200 runs/100 agents	Absolute Difference
Time	Average performance	Average performance	Average Performance
0	0.49689019	0.493536759	0.00335343
1	0.59806351	0.599996805	0.001933295
2	0.64652576	0.649976194	0.003450434
3	0.6794843	0.683718986	0.004234685
4	0.725123851	0.729286103	0.004162252
5	0.770441046	0.77553397	0.005092924
6	0.802571609	0.807086728	0.004515118
7	0.820277391	0.823452341	0.003174949
8	0.828616217	0.829822574	0.001206357
9	0.831695242	0.83220878	0.000513538
10	0.832695583	0.832932316	0.000236732
11	0.832980474	0.833313781	0.000333307
12	0.833058552	0.833491548	0.000432996
13	0.833071702	0.833491548	0.000419846
14	0.833075384	0.833491548	0.000416164
15	0.833075384	0.833491548	0.000416164
16	0.833075384	0.833491548	0.000416164
17	0.833075384	0.833491548	0.000416164
18	0.833075384	0.833491548	0.000416164
19	0.833075384	0.833491548	0.000416164
20	0.833075384	0.833491548	0.000416164
21	0.833075384	0.833491548	0.000416164
22	0.833075384	0.833491548	0.000416164
23	0.833075384	0.833491548	0.000416164
24	0.833075384	0.833491548	0.000416164
25	0.833075384	0.833491548	0.000416164
26	0.833075384	0.833491548	0.000416164
27	0.833075384	0.833491548	0.000416164
28	0.833075384	0.833491548	0.000416164
29	0.833075384	0.833491548	0.000416164
30	0.833075384	0.833491548	0.000416164

Experiential Waterfall	100 runs/50 agents	200 runs/100 agents	Absolute Difference
Time	Average performance	Average performance	Average Performance
0	0.498505468	0.501192225	0.002686757
1	0.669729837	0.666448082	0.003281755
2	0.748859757	0.748512491	0.000347266
3	0.784099785	0.784025909	7.38758E-05
4	0.798191871	0.800529526	0.002337656
5	0.803101917	0.80556234	0.002460422
6	0.804848249	0.807881438	0.003033189
7	0.805323035	0.808486363	0.003163328
8	0.805424477	0.808467736	0.003043259
9	0.805456651	0.808435901	0.00297925
10	0.805452064	0.808435901	0.002983838
11	0.805452064	0.808435901	0.002983838
12	0.805452064	0.808435901	0.002983838
13	0.805452064	0.808435901	0.002983838
14	0.805452064	0.808435901	0.002983838
15	0.805452064	0.808435901	0.002983838
16	0.805452064	0.808435901	0.002983838
17	0.805452064	0.808435901	0.002983838
18	0.805452064	0.808435901	0.002983838
19	0.805452064	0.808435901	0.002983838
20	0.805452064	0.808435901	0.002983838
21	0.805452064	0.808435901	0.002983838
22	0.805452064	0.808435901	0.002983838
23	0.805452064	0.808435901	0.002983838
24	0.805452064	0.808435901	0.002983838
25	0.805452064	0.808435901	0.002983838
26	0.805452064	0.808435901	0.002983838
27	0.805452064	0.808435901	0.002983838
28	0.805452064	0.808435901	0.002983838
29	0.805452064	0.808435901	0.002983838
30	0.805452064	0.808435901	0.002983838

Reference:

Alam, S. N. (2012). Waterfall Model Advantages and Disadvantages. Retrieved 4/7, 2014, from http://www.buzzle.com/articles/waterfall-model-advantages-and-disadvantages.html

Axelrod, R. (2003). Advancing the Art of Simulation in the Social Sciences. *Japanese Journal for Management Information Systems*, 21-40.

Chi, M. T. H., J.Feltovich, P., & Glaser, R. (1981). Categorization and Representation of Physics Problems by Experts and Novices. *Cognitive Science, 5*(2), 121-152.

Gavetti, G., & Levinthal, D. (2000). Looking Forward and Looking Backward: Cognitive and Experiential Search. *Administrative Science Quarterly, 45*, 113-137.

Goldfinch, S. (2007). Permission, Computer Failure, and Information System Development in the Public Sector. *Public Administration Review, 9*, 917.

Hahn, J., & Lee, G. (2012). *Toward a Theory of Shared Domain Knowledge in Information Systems Development: A Complex Adaptive Systems Perspective*. Working Paper.

Hax, & Majluf. (1984). *Strategic Management: an integrative perspective*.

Kauffman, S. A. (1989). *Adaptation on rugged fitness landscapes* (D. L. Stein Ed.): Addison-Wesley Publishing Company.

Levitt, B., & March, J. G. (1988). Organizational Learning. *Annual Review of Sociology, 4*, 319-340.

Lippman, S. A., & McCall, J. J. (1976). The Economics of Job Search: A Survey. *Economic Inquiry, 14*(3).

Mahaney, R. C., & Lederer, A. L. (1999). Runaway Information System Projects and Escalating Commitement. *Proceeding SIGCPR '99 Proceedings of the 1999 ACM SIGCPR conference on Computer personnel research*, 291-296.

Newell, A., & Simon, H. A. (1972). *Human Problem Solving*. Englewood Cliffs, NJ. Prentice Hall.

Porac, J. F., Thomas, H., Wilson, F., Paton, D., & Kanfer, A. (1995). Rivalry and the Industry Model of Scottish Knitwear Producers. *Administrative Science Quarterly, 40*, 203-206.

Qassim, A. A. (2007). Why Information Systems Projects Fail: Guidelines For Successful Projects. 12~15.

Sternberg, R. J. (2009). *Cognitive Psychology* (6 Ed.): Cengage Learning.

Thagard, P. (2005). *Mind: Introduction to Cognitive Science*: MIT Press.

Walsh, J. P. (1995). Managerial and Organizational Cognition: Notes from a Trip Down Memory Lane. *Organization Science, 6*(3), 279-283.