A Dynamic Bounded Rationality Model for Technology Selection in Cognition Process

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ABSTRACT

This paper attempts to overcome the defect of traditional technology selection models: the inaccurate depiction of the dynamic decision-making in technology selection with fixed time point and static preferences. To this end, a new dynamic model was created considering the preference changing over the time. The preferences were deconstructed with discontinuous functions, and a theory was developed under bounded rationality for the preference changes in four phases of cognition. It is discovered that the decision-maker may become conservative in cognition process, leading to equilibrium evolution in conservative direction over the time. The discovery was verified through a case study on the neuroscience innovation in China. The research findings shed new light on cognition and decision-making studies and open up a new way for technology selection.

Key Words: Cognition Process, Bounded Rationality, Technological Innovation, Decision-Making, Graph Model

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Introduction

Technology selection is critical to many organizations (Phaal *et al*., 2001). It has a direct bearing on competitiveness and wealth creation, especially the competitive advantages of an enterprise or a country (Khalil, 2000; Torkkeli and Tuominen, 2002; Lee and Song, 2007). With the increase in innovation cost and complexity, technology selection has become a multi-criteria decision issue and a research hotspot (Shen *et al.,* 2010). Rationality and cognition are deeply involved in technology selection (Scheiner *et al*., 2015). Thus, the key to solving technology selection problems lies in proper cognition of technologies and the rational analysis on the outcomes of selections.

Over the years, various multi-criteria modelling and analysis methods have been introduced to tackle technology selection. These approaches are either based on evaluation of technological utility/payoffs or grounded on policy analysis, preference relations or multi-objective programming. The former strategies include analytic hierarchy process (Mohanty and Venkataraman, 1993; Sloane *et al*., 2003) and fuzzy analysis (Tolga *et al*., 2005; Evans *et al*., 2013; Onar *et al*., 2015), and the latter ones include graph modelling (Han *et al*., 2012), option optimization (Roy &Karandikar, 2015), and non-cooperative game theory (Khawam *et al*., 2016). Nevertheless, these theoretically sound methods are difficult to calibrate, and computing-intensive.

Whereas scholars are still struggling to predict the technology trend, it is difficult for decision-makers (DMs) to identify the most promising technology without behavioural analysis. The difficulty arises from the setting of time point. Traditionally, the preferences of DMs are set at a fixed time point. For technology selection, however, the decision-making is a dynamic cognition process with ever-changing preferences. In this case, the pre-set time point may not reflect the reality and hinder the

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selection efficiency.

In light of the above, this paper aims to explore dynamic equilibrium changes over the time, and adapt the traditional technology selection model to these changes, thereby enhancing the reliability of technology analysis. For these purposes, the preferences were constructed by discontinuous functions and bounded rationality (Herbert Simon, 1982), and a four-phase model was built four preference changes in the cognition process. These new tools and principles make it possible to rationally expand technology selection analysis.

Methodology

Graph model for conflict resolution

The classical theory of graph model (hereinafter referred to as the graph model) for conflict resolution lays the basis for the novel dynamic analysis in technology selection. Inspired by on the set theory and graph theory, the graph model is a branch of the game theory that predicts the trend of conflicts and counter measures through mathematical modelling of real-world problems (Kilgour *et al.*, 1987; Fang *et al.*, 1993). In this model, the DMs' preferences are expressed as binary relations rather than payoffs, and their strategy options are transformed into a preference sequence; then, the evolution of the game state is deduced according to the preferences, yielding a clear equilibrium path and strategy option (Hipel *et al.*, 2011). The graph model has been widely adopted to solve resource conflicts (Madani *et al.*, 2011; He *et al.*, 2014; Yu *et al.*, 2015), trade negotiations (Hipel and Walker, 2011) and technological issues (Han *et al.*, 2012).

Analytical process

The first step of graph model-based game analysis is to collect the basic information and behaviour strategies of the DMs with different goals. On this basis, the feasible state should be determined, and the real-world problem be transformed into a mathematical one. Then, the equilibrium solution should be derived from the DMs' preferences by matrix operations and graph theory, and the evolution of the game should be determined through stability analysis.

Each of the DMs involved in the game is assumed to be sufficiently rational to behave to the self-benefit. However, it is the collective analysis and judgement of multiple DMs that determines the final outcome of the game and the final equilibrium state, that is, the stable outcome most likely to be accepted by all players. Known as the most classical equilibrium, the Nash equilibrium (Nash, 1950) is defined as follows: For DM_i $i \in N$ and state $s \in S$, $R_i^+(s) = \phi$ holds; Thus, for DM_i, state s_t is Nash stable and denoted as $s_t \in S_i^{NASH}$. Nash equilibrium means that the DMs cannot get better status through unilateral enhancement.

Preference Analysis in Cognition Process

Preference changes in time sequence

During the cognition process, the DMs' preferences tend to change with the time. The changes in the brain during the cognition process can be detected as shown in Figures 1 and 2, thanks to neuroscience technologies of Blood-Oxygen-Level Dependent (BOLD) imaging and Event-Related Potential (ERP) analysis. It can be seen that, the blood flow and electrical activities vary with the elapse of time, resulting in different feedbacks, preferences, decisions and actions. That is why the decision-making in technology selection is a time-varying dynamic process, instead of a sequence of discrete behaviours occurring at a fixed time point.

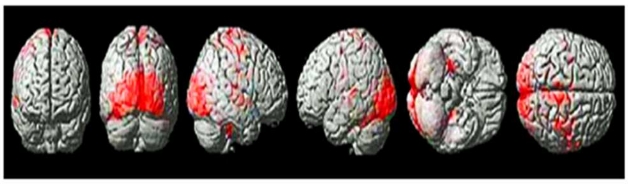

Figure 1. Functional magnetic resonance imaging (fMRI) results on the brain's cognition process

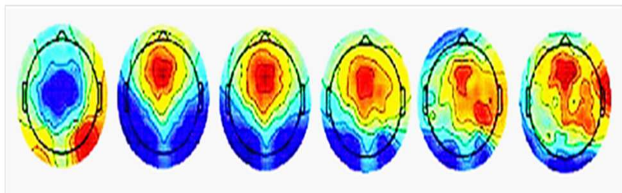

Figure 2. Brain electrical activity mapping (BEAM) results on the brain's cognition process

According to the bounded rationality theory, the clarity of options is positively correlated with the amount of information being collected (Simon, 1982). When a DM ponders over his/her problem, the source of his/her preferences gradually shifts from intuition, emotion to rationality. Thus, the decision-making process can be divided into four phases: the habit phase, the emotion phase, the maximum payoff phase, and the minimum risk phase.

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In the habit phase, the DM's action is mainly driven by habit or intuition. The action could be a quick reaction under time pressure or an action without hesitation. In the emotion phase, the DM's action is motivated by emotion after a short period of reflection. He/she is more concerned about feelings than payoffs. In the maximum payoff phase, the DM's action is prompted by bounded rationality on a small scale. The number of options may grow as he/she aims to maximize personal payoffs. The term "small scale" reflects that the DM still pursues short-term and local/personal benefits. In the minimum risk phase, the DM's action originates from bounded rationality on a large scale. The number of options may shrink as he/she tries to minimize group risks. The term "large scale" means the DM now focuses on long-term goals, others' benefits and potential risks.

To represent the four-phase process, the author created a discontinuous function with four thresholds, and used it to qualitatively simulate the real-world conflict evolution (Figure 3). The discontinuous function can be expressed as: $P(t)=f(t)+\delta$

Where P is preference attitude; t is time; δ is an uncertain effect or new possibility. The preference attitude can be measured by its radicalness or conservativeness. As time goes, some new factors involved in the conflict may arise unpredictably, leading to option changes that affect DMs' preferences and attitudes.

Depending on time pressure and other conditions, a decision-making process may stop at any time point. Thus, not every technology decision covers all four phases. Furthermore, a DM may stop at any of the four phases if he/she did not think of all four phases in advance. In addition, the duration of each phase varies with the DMs. As more and more factors are taken into consideration, the habit and emotions phases tend to be shorter than the maximum payoff and minimum risk phases.

Preference evaluation

In essence, the preference is the combination of emotion and attitude based on expectations/prospects, and the driving force pushing DMs towards time-varying options. The key influencing factors of preference evolution can be identified as follows.

Suppose n DMs are involved in a conflict. For DM_i, ($i \in \{1,2,\dots,n\}$), the final outcome is shaped by his/her own action, other DMs' actions, and random events. In other words, an outcome o is determined by the action of DM_i, denoted as a, the actions of other DMs, denoted as *sp*, and random events, denoted as *re*.

Let O be the set of all outcomes from the perspective of DM_i. Since DM_i's action is controllable in his/her own eyes, the value of outcome *o=(a, sp, re)* reflects the emotion, wealth, and regret associated with other DMs' options. Similarly, *sp* and *re* are subjectively evaluations,

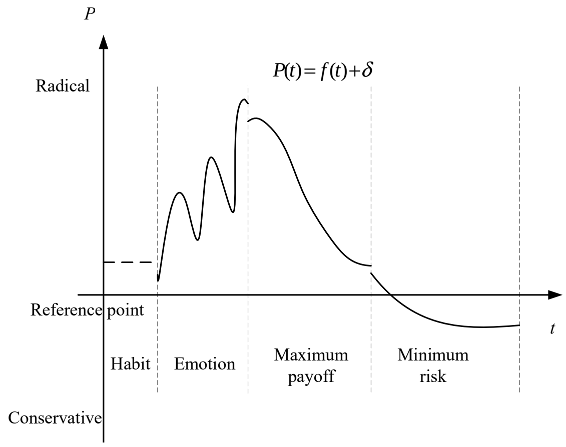

Figure 3. Discontinuous function of decision phases (Note: The dotted line in the habit phase describes attitude uncertainty.)

Table 1. Factors involved in evaluation of an outcome for DM_i

Factor	Definition	
o	Outcome of the conflict, i.e. the combination of each DM's options.	
$V(o)$	Evaluation of outcome o. Note that $V(o)$ varies with time.	
a	Typical action/option that may be adopted by DM_i.	
$U_i(a)$	Utility of action a for $\mathrm{DM_i}$,.$U_i(a) = E_i(a) + W_i(a) - R_i(a)$.	
	$\mathrm{E}_i(a)$	$\mathrm{DM_i}$'s emotional gain through action a.
	$W_i(a)$	$\mathrm{DM_i}$'s financial gain through action a, i.e. wealth estimate.
	$R_i(a)$	$\mathrm{DM_i}$'s regret of action a, i.e. other actions can lead to better results.
sp	Speculation about the possibility of other DMs' actions.	
re	Random events, including potential accidents and risks. These events occur more frequently over the time, and affect the evaluation of outcome o.	

because other DMs' actions and random events are uncontrollable to DM_i.

It is assumed that each DM's decision concerning the selection of action a is based on the relative values of an evaluation of his/her own action, other DMs' actions and random events. The evaluation is denoted as $V(o) = V(a, sp, re)$. As the rationality changes in different phases, the way that $V(o_k)$ is calculated also varies with time, reflecting the changes in DM_i 's attitude, perception, and strategy.

The factors involved in the evaluation $V(o)$ are listed in Table 1. Note that, within O, DM_i's preference ranking is always determined by the relative value of $V(o_k)$.

If DM_i has a regret $R(a)$ over an action, he/she will develop a preference for actions that always produce an acceptable outcome over radical actions. Because of bounded rationality, individuals often cannot identify all the possibility or make accurate evaluations of a complex conflict (Simon, 1982). According to prospect theory (Kahneman, 1979), people are more sensitive to future losses than a similar amount of future gains, that is, they are more concerned about the risk of losses. In view of these, it is assumed that DMs are eagerly looking for the minimal risk and optimal utility.

The DM_i's speculation (sp) about the possibility of other DMs' actions is not precise under bounded rationality. Thus, the DM_i's evaluation of each outcome should be adjusted by $f(sp, re)$, to lower the relative evaluation of risky actions and increase the that of conservative actions. As stated in entropy theory (Georgescu-Roegen, 1993; Shannon, 2001), uncertainty will not decline in an isolated system without external interference. If the entire conflict model is considered as a system, then the risks induced by random events will increase with the time. Therefore, $f(sp, re)$ is an intuitively determined weighting factor that may change over the time.

Dynamic preference evaluation model

Through the above discussion, this section sets up a dynamic preference evaluation model considering the four phases of the preference attitude in the cognition process.

(1) The intuition phase (no evaluation)
Within a short period of time, a DM is unclear of his/her preferences for possible outcomes. In this phase, he/she has to act by intuition, a mirror of previous experience, habits and reactions. Thus, the decision-making is basically unconscious (Simon, 1987).

(2) The emotion phase ($V(o) = E(a)$)
After a while, emotion takes over the decision-making mechanism. Without logical thinking, the DM has limited evaluation ability and takes actions based on feelings. Some of these actions may help restore equilibrium. If so, emotion is even more influential than rationality (Izard, 1993; Dolan, 2002). Besides, the emotion-driven DM emphasizes immediate feedbacks over future return, failing to consider possibilities and risks. Therefore, the decision-making can be expressed as $V(o) = E(a)$ or $V(o) = E(a) + E(a)$ (considering the wealth effect of outcomes) in this phase.

(3) The small-scale rationality phase ($V(o) = f(sp, re) * [E(a) + E(a)]$)
As time passes, rationality begins to take effect, enabling the DM to make realistic evaluations. Since neuroscience and social science suggest that humans are more optimistic than realistic (Sharot, 2011), the DM's preference tends to be radical, at least in the beginning. The preference gradually grows conservative, with the growing awareness of risks over the time.
(4)The large-scale rationality phase ($V(o) = f(sp, re) * [E(a) + E(a) - R(a)]$)
In this phase, the DM reflects deeply on group profits, long-term relationship and potential revenues/costs. Thus, Regret becomes an important part of the evaluation. To avoid regret, the DM predicts the possibilities of all outcomes and takes pertinent measures. As a result, his/her preference turns more and more conservative.

Case Study

A case study of neuroscience development in China is employed to demonstrate that the four phases dynamic model reflect the actual situation of technological innovation. In order to make the study more representative, the authors spent five years visiting 213 neuroscience research centers, hospitals and institutes, and tracked 576 researchers and government officials through field investigation and interview. Here, a four-phase dynamic model of neuroscience innovation is analyzed based on the data collected in the visits, investigations and interviews.

Table 2. Conflict model of two DMs and five options

DMs	Options	Explanation
Government (G)	Maintenance(M)	Maintain the status quo, and provide no substantial assistance in technological innovation.
	Funding(F)	Provide financial supports (e.g. grants and low-interest loans) to new technology owner.
	Policymaking(P)	Offer policy supports (e.g. tax deduction, exemption and free land) to new technology owner.
Research community (R)	Innovation(IN)	Work on technological innovation and promote new technology.
	Improvement(IM)	Improve the existing technology instead of pursuing breakthroughs.

Table 3. Feasible states

DMs	Options	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8
Government (G)	Maintain (M)	Y	N	N	N	Y	N	N	N
	Funding(F)	N	Y	N	Y	N	Y	N	Y
	Policy(P)	N	N	Y	Y	N	N	Y	Y
Research community (R)	Innovation (IN)	Y	Y	Y	Y	N	N	N	N
	Improving (IM)	N	N	N	N	Y	Y	Y	Y

(Note: Y means the state is selected by the DM; N means the opposite.)

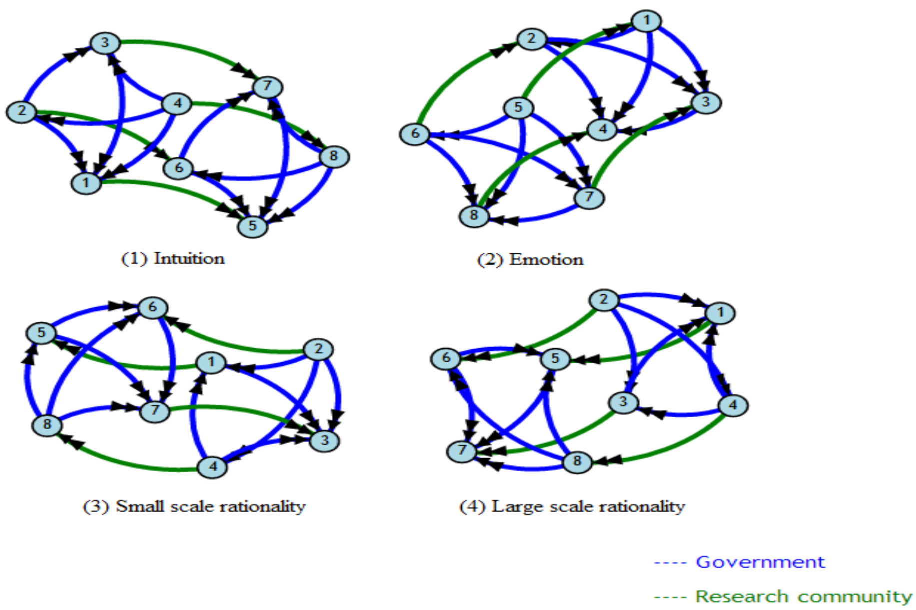

Figure 4. States transition in cognition process (*Note: Bold arrow lines stand for unilateral improvements in different phases.*)

Modelling

There are two main players in a conflict of neuroscience innovation, namely the government and the research community. The government acts as the promoter of new technology application, while the research community produces technological innovation. Considering the information on neuroscience innovation players, the author set up a conflict model of two DMs and five options (Table 2).

Since each option can be either selected or rejected, there are a total of 32 (25) mathematically possible states. Nonetheless, many of these states are infeasible in reality. For example, the government cannot maintain the status quo (M) and provide funding (F) or policy support (P) at the same time. Besides, the research community is assumed to choose between innovation (IN) and improvement (IM) for the sake of simplicity. In light of the information on the government and the research community, all unfeasible states were removed, leaving 8 feasible states. The feasible states are listed in Table 3.

Equilibriums analysis

The preference sequence in different phases was calibrated and calculated, according to the results of data tracking and the evaluation function $V(o) = f(sp, re) * [E(a) + E(a) - R(a)]$. And they are shown in Table 4.

Based on the feasible states, DMs' preferences, the comprehensive analytical results were obtained by the graph model for conflict resolution plus (GMCR+) (Kinsara *et al*., 2015). The resulting state transitions of technology selection are illustrated in Figure 4. The Nash

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Table 4. Preferences in cognition process

Phase	DMs	Preferences
(1) Intuition	Government (G)	S1>S5>S3>S2>S4>S7>S6>S8
	Research community (R)	S8>S4>S6>S2>S7>S3>S5>S1
(2) Emotion	Government (G)	S4>S8>S3>S2>S7>S6>S1>S5
	Research community (R)	S4>S2>S3>S1>S8>S6>S7>S5
(3) Small scale rationality	Government (G)	S3>S1>S4>S2>S7>S6>S5>S8
	Research community (R)	S8>S6>S4>S2>S3>S7>S5>S1
(4) Large scale rationality	Government (G)	S1>S3>S4>S5>S2>S7>S6>S8
	Research community (R)	S8>S6>S7>S4>S2>S3>S5>S1

Table 5. Equilibriums in cognition process

Phases	Nash equilibriums
(1) Intuition	S5: (Maintain, Improving)
(2) Emotion	S4: (Funding & Policy, Innovation)
(3) Small scale rationality	S3: (Policy, Innovation)
(4) Large scale rationality	S7: (Policy, Improving)

equilibriums in the cognition process are given in Table 5 to depict the technology trend in reality.

The technology selection in neuroscience was acquired in accordance with the state transitions and Nash equilibriums in different phases. In the beginning, both the government and the research community instinctively chose to maintain the status quo and use the old technology. Soon, both of the DMs became positive to the new technology. The government started issuing grants and favourable policies, while the research community worked on technological innovation. However, later, more uncertainties and risks arose in technological innovation, forcing the government to lower the financial supports and the research community to return to the old technology. As a result, the technological innovation reached a plateau. To sum up, the DMs' preferences to technological innovation turned conservative over the time, leading to an equilibrium evolution in conservative direction. To solve the problem, the government should be more patient for innovation and the research community should to shorten the cycle of technological production.

Conclusions

To enhance the decision-making on technological innovation, a dynamic model was proposed considering the time varying preferences, and a four-phase theory was developed with a discontinuous function to model the evolution of conflict. The four phases, namely, intuition, emotion, small-scale rationality and large-scale rationality, reflect the four changes of preferences during the decision-making process. Then, a tendency of conservatism was observed in technology selection.

To further understand technology evolution in cognition process, the preference was regarded as the combination of emotion and attitude based on expectations/prospects. The outcomes were ranked according to $V(o)$, which shifts from intuition to large-scale rationality ($V(o) = f(sp, re) * [E(a) + E(a) - R(a)]$). It is discovered that the risk-averse mind-set appears as more factors are taken into account over the time, leading to equilibrium evolution in conservative direction.

Moreover, the case study shows that the DMs' preferences to technological innovation turned conservative over the time, leading to an equilibrium evolution in conservative direction. To solve the problem, the government should be more patient for innovation and the research community should take measures to shorten the cycle of technological production. Performs in technological innovation can be improved by identified important factors within cognition process.

The future research will find more convincing demonstrations to our theoretical framework. As time point is an important issue in decision making, questionnaire surveys, statistical analysis and improved mathematical model could be further developed to expand this research field.

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