View metadata, citation and similar papers at core.ac.uk
brought to you by CORE
provided by AIS Electronic Library (AISeL)

Association for Information Systems
AIS Electronic Library (AISeL)

AMCIS 2009 Proceedings

Americas Conference on Information Systems (AMCIS)

2009

Evaluation of Decision Rules Used for IT Portfolio Management: An Inductive Approach

Prasanna P. Karhade
University of Illinois at Urbana-Champaign, karhade@illinois.edu

Michael J. Shaw
University of Illinois at Urbana-Champaign, mjshaw@illinois.edu

Ramanath Subramanyam
University of Illinois at Urbana-Champaign, rsubrama@illinois.edu

Follow this and additional works at: http://aisel.aisnet.org/amcis2009

Recommended Citation
Karhade, Prasanna P.; Shaw, Michael J.; and Subramanyam, Ramanath, "Evaluation of Decision Rules Used for IT Portfolio Management: An Inductive Approach" (2009). *AMCIS 2009 Proceedings*. 154.
http://aisel.aisnet.org/amcis2009/154

This material is brought to you by the Americas Conference on Information Systems (AMCIS) at AIS Electronic Library (AISeL). It has been accepted for inclusion in AMCIS 2009 Proceedings by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

Evolution of Decision Rules Used for IT Portfolio Management: An Inductive Approach

Prasanna P. Karhade
University of Illinois at Urbana-Champaign,
1206 South Sixth Street, Champaign IL 61820.
karhade@illinois.edu

Michael J. Shaw
University of Illinois at Urbana-Champaign,
1206 South Sixth Street, Champaign IL 61820.
mjshaw@illinois.edu

Ramanath Subramanyam
University of Illinois at Urbana-Champaign,
1206 South Sixth Street, Champaign IL 61820.
rsubrama@illinois.edu

ABSTRACT

IT portfolio management and the related planning decisions for IT–dependent initiatives are critical to organizational performance. Building on the logic of appropriateness theoretical framework, we define an important characteristic of decision rules used during IT portfolio planning; rule appropriateness with regards to the risk-taking criterion. We propose that rule appropriateness will be an important factor explaining the evolution of rules over time. Using an inductive learning methodology, we analyze a unique dataset of actual IT portfolio planning decisions spanning two consecutive years within one organization. We present systematic comparative analysis of the evolution of rules used in planning over two years to validate our research proposition. We find that rules that were inappropriate in the first year are being redefined to design appropriate rules for use in the second year. Our work provides empirical evidence demonstrating organizational learning and improvements in IT portfolio planning capabilities.

Keywords: IT portfolio management, decision rules, inductive learning, logic of appropriateness

INTRODUCTION

IT portfolio management and decision-making for IT–dependent initiatives[1] is critical to organizational performance (Jeffery and Leliveld 2004, Piccoli and Ives 2005). Organizations are today trying to leverage a plethora of emerging technologies in the Web 2.0 domain. These Web 2.0 applications have the potential to offer a variety of benefits (McAfee 2007). Given the high impact of these applications, the proportion of these Web 2.0 investments are growing in size. Given that the terrain of these Web 2.0 applications is constantly evolving, executives are expected to adapt their corresponding decision making for such portfolios of Web 2.0 applications (McAfee 2007). Portfolios of IT-dependent initiatives, including Web 2.0 inititaives, have the potential to deliver high business value (Maizlish and Handler 2005) but are often plagued with several factors leading to low success rates. Among other factors, low success rates have been often attributed to inadequate attention being allocated to risk management early during planning (Boynton and Zmud 1987). Managing risks during planning is relevant from an IT governance standpoint. IT itself is constantly evolving; especially the technological terrain in Web 2.0; investments in IT can lead to significant organizational changes. IT initiatives require significant redesign to an organization's business processes including processes that interact with customers and suppliers. Given these changes that ensue due to IT initiatives, refinements to IT portfolio management capabilities are essential.

We find that emphasis on risk mitigation early during planning continues to be a relatively understudied research area. Decision making during planning often results from planners answering for themselves the question: "What does a person like me do in a situation like this?" Building on the theoretical framework of the logic of appropriateness (March 1994) which contrasts the expected utility models for decision making, we define an important characteristic of rules; rule appropriateness with regards to the risk-taking criterion (March and Shapira 1987). We propose that appropriateness of rules will be an important factor explaining the evolution of rules over time. Our work contributes to the research literature in the following ways. We analyze a unique longitudinal data set of actual portfolio decisions (proposed initiatives are rejected or

[1] IT-dependent initiatives are broad organizational efforts. Such initiatives often lead to the creation of several smaller IT development or integration projects.

partially approved or fully funded) within one organization spanning two consecutive years. We adopt an inductive learning methodology which is best suited for uncovering tacit decision making rules. We present comparative findings which demonstrate refinements to decision rules. In two of the three comparative scenarios presented, we find that rules that were inappropriate in the first year are being refined to develop appropriate rules in the second year's planning session. These findings provide evidence of organizational learning with regards to the use of appropriate rules over time. Thus, our research provides empirical evidence highlighting the role of rule appropriateness in explaining the evolution or refinement of decision rules over time.

BACKGROUND

IT Portfolio Management and Rules

IT portfolio management practices are used to improve the return on planned and existing IT initiatives (Jeffery and Leliveld 2004). IT planners manage IT assets as a portfolio; similar to investments in a financial portfolio (Maizlish and Handler 2005). IT planners aim to improve performance of their portfolios by aligning IT initiatives (Sabherwal and Chan 2001) with business objectives and by managing risks (McFarlan 1981). Two predicaments faced by planners are presented in Figure 1. First, *Gresham's law of planning* states that "daily routine drives out planning" (March and Simon 1958, p.185). Planners should ensure that they devote their limited attention to key planning concerns and not be distracted by tactical plan-implementation issues. Second, *the planning paradox* suggests that planners are expected to complete planning rapidly; expediting planning can lead to the development of inappropriate plans; effectively reducing the likelihood of success during implementation (Lederer and Sethi 1996).

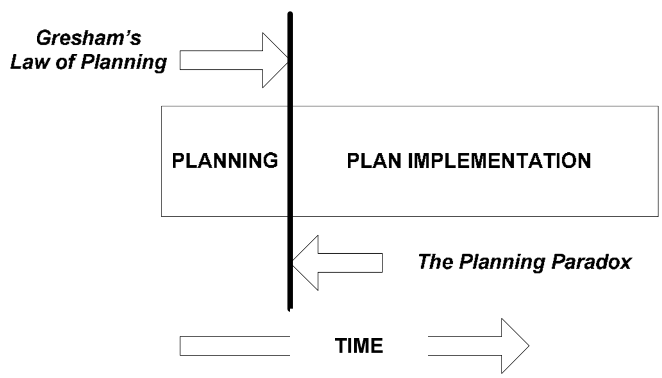

Figure 1. Issues in Planning

Decision rules address these twin challenges associated with planning (Heugens and Bosch 2004) via three mechanisms. *First,* rules can alleviate problems associated with the bounded rationality (Simon 1955); potentially attenuating the planning paradox. Second, rules can facilitate knowledge sharing for improved coordination among diverse groups by routinizing complex organizational behavior (Tsoukas 1996). Third, implementation of large initiatives requires delegation of tasks to a set of actors who might not necessarily share the objectives of the planners. Planners can use rules as incentive alignment mechanisms (Eisenhardt 1989) by rewarding rule-following and penalizing rule-defiant behavior. Rules can be central to organizational learning (Levitt and March 1988) where new experiences guide the refinement of rules over time.

Logic of Appropriateness

March (1994) proposes that decisions are shaped by situational recognition, one's identity, and the application of rules. Decisions result from people answering for themselves the question, *"What does a person like me (1: Identity) do (2: Rules) in a situation like this (3: Recognition)?"* Logic of appropriateness which contrasts the dominant expected utility models (Luce and Raiffa 1957) serves as the theoretical framework in our research.

Identity: Business strategies adopted by an organization are used to develop distinct identities for organizations. The Miles and Snow (1978) Defender-Prospector-Analyzer classification is one such typology. Defenders are risk-averse; stress efficiency of operations; emphasize a narrow domain by aggressively controlling niches in their industry and engage in little new product development (Miles and Snow 1978). Prospectors are risk-takers; constantly explore emerging opportunities and stress new product development (Miles and Snow 1978). Analyzers who exhibit characteristics of both Defenders and Prospectors (Miles and Snow 1978) are argued to be risk averse.

Recognition: Mitigating risks during planning (the situation here) is arguably appropriate behavior from an IT governance standpoint. Two perspectives on risk-taking (March and Shapira 1987) guide the conceptual development rule appropriateness: (1) planners perceive risk-taking as a key expectation of their jobs and (2) planners take risks willingly as they believe risk can be controlled. Managers make a sharp distinction between gambling (where the odds are exogenously determined) and risk-taking (where managerial effort can control risks). Before plan implementation commences, executives should exert effort (to gather information or develop skills) enabling them to manage risks (Lambert 1986).

Appropriate Rules: High/medium risk initiatives can place an organization under considerable financial stress. Appropriate behavior during planning requires planners to arrive at decisions on high/medium risk initiatives only after assessing risk mitigation mechanisms devised to control risk (Boynton and Zmud 1987). Planners who approve proposed high/medium risk initiatives without ensuring the presence of risk mitigation mechanisms are gambling and behaving inappropriately. Rejecting high/medium risk initiatives; without exerting effort to manage those risks would also be inappropriate as planners are expected to take some risks during planning. High/medium risk initiatives should be appropriately selected only after ascertaining that some risk mitigation mechanisms are present to manage these sources of risks (March and Shapria 1987).

Definition of Rule Appropriateness: Addressing sources of risk during planning is critical (Boynton and Zmud 1987). Decision rules that show evidence suggesting that risk mitigation mechanisms are present before approving high/medium risk initiatives are defined to be appropriate with regards to risk-taking (March and Shapira 1987).

Inappropriate rules are more likely to be refined over time before being reused in future planning sessions. Appropriate rules will also deserve refinement, especially if they lead to unsatisfactory performance outcomes.

Research Proposition: Rule appropriateness will be a key factor explaining the evolution of decision rules over time.

METHODOLOGY

We choose a large, public Fortune 10 organization for our study. This organization is head quartered in the United States, operates in 50 locations worldwide, and employs more than 39,000 people. This organization is experiencing tremendous growth and its revenues in 2007 were more than 16 billion U.S. dollars. We adopt an inductive learning methodology to uncover the decision rules used during planning.

Data

Data were collected based on interaction with five key informants within this organization (Vice President and CIO, and four senior executives in the CIO team). For triangulation, data were collected by the following methods; content analysis of information presented in the annual reports; face-to-face semi-structured interviews with all key informants spanning twenty hours; unobtrusive participation in a planning session lasting two hours; conference calls with all the key informants spanning forty hours; and exchange of confidential documents between the researcher team and our key informants. Based on our qualitative understanding of the business strategies chosen by this organization, we classified it as an Analyzer. Our interpretation was unanimously validated by the key informants at this organization. Portfolio data were gathered from the field based on our collaboration with the key informants. The unit of analysis used in this study, an IT-dependent initiative, is defined as a large organizational effort (Piccoli and Ives 2005) involving significant investments, design of information systems, most likely the redesign of business processes. We analyze IT portfolio data spanning two consecutive years (presented in Table 1). These portfolios contain 57 IS-dependent initiatives for year one and 106 initiatives in year two. The portfolio for the first year contained 13 initiatives estimated to cost less than one hundred thousand dollars; 9 initiatives estimated to cost over one million dollars and 35 initiatives estimated to cost more than one hundred thousand and less than one million dollars. The portfolio for the second year contained 64 initiatives estimated to cost less than one hundred thousand dollars; 13 initiatives estimated to cost over one million dollars and 29 initiatives estimated to cost more than one hundred thousand and less than one million dollars. Planning decisions were based on a careful consideration of benefit, risk and mitigation capabilities associated with proposed initiatives. For instance, prior literature (for e.g. Broadbent et al 1999) has suggested that managing the business process redesign implications of large IT-dependent initiatives is critical. Thus this is important source of risk which often needs to be managed upfront. Thus considering such capabilities (for e.g. Business Process Redesign (BPR) Work done) before commencing on large IT dependent initiatives, like the ones we consider in this study can be critical. Similarly, we include various organizational mitigation capabilities to comprehensively understanding decision making during strategic IS planning.

Measure Development

Characterizing Risks

We adopt McFarlan (1981)'s approach for assessing the risk of IS-dependent initiatives.

Initiative Size: This attribute was measured based on the estimated investment. The risk associated with an initiative increases with its size (McFarlan 1981). This variable was assigned three values: Low (investment less than one hundred thousand dollars), Medium (investment greater than one hundred thousand dollars and less than one million dollars) and High (investment was greater than one million dollars).

Inputs to the planning process			**Outputs of the planning process**
	Benefits Associated With Initiatives	**Risks/Risk Mitigation Mechanisms**	**Portfolio Decisions**
Year One (n=57)	Initiative Type OSS Initiative (79%) MIS Initiative (53%) IOS Initiative (49%) SDSS Initiative (32%) Process Benefits (82%)	*Initiative Structure* (Low Structure = 32%, High Structure = 68%) *Initiative Size* (Low = 23%, Medium = 61%, High = 16%) *Prior Experience* (Low = 67%, Medium = 23%, High = 10%) *BPR Work Done* (16%) *BPR Resources Committed* (23%)	Reject (25%) Partially Approve & Fund (30%) Fully Approve & Fund (45%)
Year Two (n=106)	Initiative Type OSS Initiative (46%) MIS Initiative (19%) IOS Initiative (41%) SDSS Initiative (20%) Process Benefits (89%)	*Initiative Structure* (Low Structure = 58%, High Structure =42 %) *Initiative Size* (Low = 60%, Medium = 27%, High = 13%) *Prior Experience* (Low = 20%, Medium = 33%, High = 47%) *BPR Work Done* (10%) *BPR Resources Committed* (43%)	Reject (18%) Partially Approve & Fund (25%) Fully Approve & Fund (57%)

Table 1. Data Summary

Initiative Structure: Some initiatives, by their very definition, are well-defined, in terms of their inputs and outputs. The corresponding organizational tasks required to convert inputs to the desirable outputs, are relatively straightforward (Eisenhardt 1985). Initiatives of high structure (McFarlan 1981) are less risky when compared to initiatives with low structure. Initiatives where the expected outputs are vulnerable to change are low structured and inherently risky. This variable was assigned two values: high (well-defined objectives) and low (objectives of the initiative are fluid).

Prior Experience: As the familiarity of an organization with a technology increases, the likelihood of encountering technical problems reduces. Higher the prior experience with technologies used in the execution of an initiative, lower the risk associated with that initiative (McFarlan 1981). This variable was assigned three values: low (new application development with emerging technologies), medium (non-trivial improvements to standard technologies) and high (relatively simple applications of standard technologies).

Characterizing Benefits

Initiative Type: Investments in IS can provide benefits to organization in many ways[2]. Based on the various types of benefits that can be extracted from IS initiatives, detailed descriptive information on proposed initiatives was used assign this variable, the following values (Sabherwal and Chan 2001): inter-organizational systems (IOS) initiative and/or marketing information systems (MIS) initiative and/or strategic decision support systems (SDSS) initiative, and/or operational support systems (OSS) initiative.

Process Benefits: IS-dependent initiatives can enable process improvements (Broadbent et al. 1999). This variable was assigned a value of 1 when the initiative enabled business process improvements and a value of 0 otherwise.

Characterizing Risk Mitigating Factors

BPR Work Done: Performing business process redesign before starting initiatives is critical to minimizing process risks (Broadbent et al. 1999) related to the execution of initiatives. This variable was assigned a value of 1 when initiative related business process redesign work was completed and a value of 0 otherwise.

BPR Resources Committed: IS initiatives can either constrain or facilitate BPR initiatives (Broadbent et al. 1999). Committing resources for undertaking BPR before starting technology-dependent initiatives can be a risk mitigation factor. This variable was assigned a value of 1 when resources were assigned to proposed IS-dependent initiatives for conducting BPR and a value of 0 otherwise.

Portfolio Decisions

Decisions for each proposed IS-dependent initiative belonged to one of the following three classes: initiatives were (1) rejected; (2) partially approved and supported with partial funding; (3) fully approved and funded.

Inductive Learning

Decision trees have been used to study organizational decision-making (Quinlan 1986, 1990). In its general form, the inductive learning process contains three phases: (1) instance space; (2) algorithm used for learning; (3) output describing the target concept. The instance space is an n-dimensional space where each instance is described by n attributes and a classification concept. For every run of the learning algorithm the instance space is represented by a training sample. In our case the target concept is a description of the induced managerial decision-making process. The purpose of induction is to discover the most precise approximation of the target concept. From an instance space, an approximation of the target concept, called hypothesis is induced. Each such approximation forms an instance in the hypothesis space. Each hypothesis represents a more or less credible approximation of the target concept. The decision tree representation which has been previously applied to discover decision-making processes, describes the target concept using a set of conjunctives (Quinlan 1986, 1990). Trees create an ordering among the attributes characterizing examples that belong to a particular class and the ones that do not. The tree-based inductive learning approach discovers and represents the knowledge contained in a decision process in a comprehensive and structured way (Shaw and Gentry 1988, 1990). Decision trees possess predictive validity comparable to other statistical classifiers. Given this high descriptive validity, decision trees offer unique advantages over statistical classifiers. An interpretation of the paths in the decision tree provides insights concerning the underlying structure of the data, which highlights a collection of attributes used in the classification procedure (Tessmer, Shaw and Gentry 1993,

[2] A rigorous quantification of benefits associated with initiatives (such as a ROI) would be desirable. But often arriving at quantification like this is extremely difficult and unrealistic especially given the planning paradox.

Gentry *et al.* 2002). The number of examples classified on a particular decision path guides us in the discovery of patterns in the decision-making process (Tessmer et al. 1993). The length and the width of the decision trees capture the complexity of the underlying decision process. A randomly drawn sample of 70% of the portfolio data was used for training and the prediction accuracy of the induced model was tested on a disjoint randomly drawn sample of 30% of the total size. Every random sample was selected such that all the classes of the decision were represented; ensuring purity of induced trees. Trees were randomized ten times at this stage to study structural stability and to compare the prediction accuracy of the induced models. To further improve the validity of the findings, the same analysis was conducted using an 80% training sample and a 20% testing sub sample. All the decision trees were generated by using the C4.5 inductive learning algorithm (Quinlan 1986, 1990). A decision tree with high structural stability and prediction accuracy was selected as the best approximation of the underlying, unknown decision making process. Steps taken to choose the best representative are presented in Appendix 1.

RESULTS

Key Findings (Year One)

Figure 2 presents the best representative model for the first year's planning session. These attributes were selected (in the order in which they appear) by the C4.5 classification algorithm (Quinlan 1990) based of the amount of information they provided regarding the output classes (i.e. the various decisions). The interpretation of this decision model reveals the following findings. In total, sixteen rules were sufficient to compactly represent the underlying decision-making process for the fifty seven choices made by planners during this planning session. The average strength of the rules was 3.56 choices per rule. The average length of the decision rules was 3.875 implying that on average more than 3 decision-making criteria were considered before making choices. The *Analyzer* emphasizes both efficiency improvements and exploring emerging opportunities. Balancing these two conflicting organizational goals is often challenging. The best representative decision model reveals a balanced decision-making paradigm given that of the 14 decisions attributes in the model half pertained to characterizing benefits and the other half pertained to mitigating risks. This Analyzer's decision space was also relatively complex; proposed initiatives were not only rejected or approved; but some promising initiatives are also partially supported with partial funding. As should be evident based on the length and width of the decision tree, we believe this decision model faithfully captures the underlying complexity of the decision-making process. Initiative size was *the most discriminating attribute* and different decision-making criteria were used to decide upon initiatives within the three size categories. The *main path in this decision tree*, the decision rule with the highest strength, was one that partially approved and funded eight medium sized initiatives proposed to deliver strategic benefits. Given that this decision rule did not include any risk mitigation mechanisms to manage risks associated with these substantial medium-sized investments; this decision rule was judged as being inappropriate with regards to risk-taking criterion. Of the total 16 induced decision rules, 7 decision rules (43%) were judged as being appropriate based on the risk-taking criteria. In total, 10 initiatives were decided upon using these appropriate decision rules (22%). Of the 28 proposed initiatives approved in this planning session 8 were approved using appropriate decision rules.

Key Findings (Year Two)

The second year's best representative model was chosen using a similar methodological approach as presented in the appendix. The most discriminating classification attribute for the selected decision model presented in Figure 3 is "SDSS Initiative" where as now "Initiative Size" emerged as a level two decision-making criteria. Again, these attributes were selected (in the order in which they appear) by the C4.5 classification algorithm (Quinlan 1990) based of the amount of information they provided regarding the output classes (i.e. the various decisions). Though the size of the decision problem has increased, a more compact decision model emerged as a satisficing representative of the underlying unknown decision-making process. As seen by the size of the decision model, this model is compact when compared to the previous year's decision model. The average strength of the decision rules is 8.83. The average length of the decision rules in year two is 3.75.The comparison of these two models along the dimension of appropriateness with regards to risk-taking reveals some interesting insights. The second year's decision model has fewer appropriate decision rules: only 3 of the 12 decision rules (25%) are appropriate based on the risk-taking criterion. Given that the average strength of the rule has increased, a larger proportion of choices are made using these fewer decision rules. In the first year, 10 of the total 44 initiatives (22%) were decided upon using appropriate rules where in the second year 9 of the total 31 initiatives (29%) were decided upon using appropriate rules.

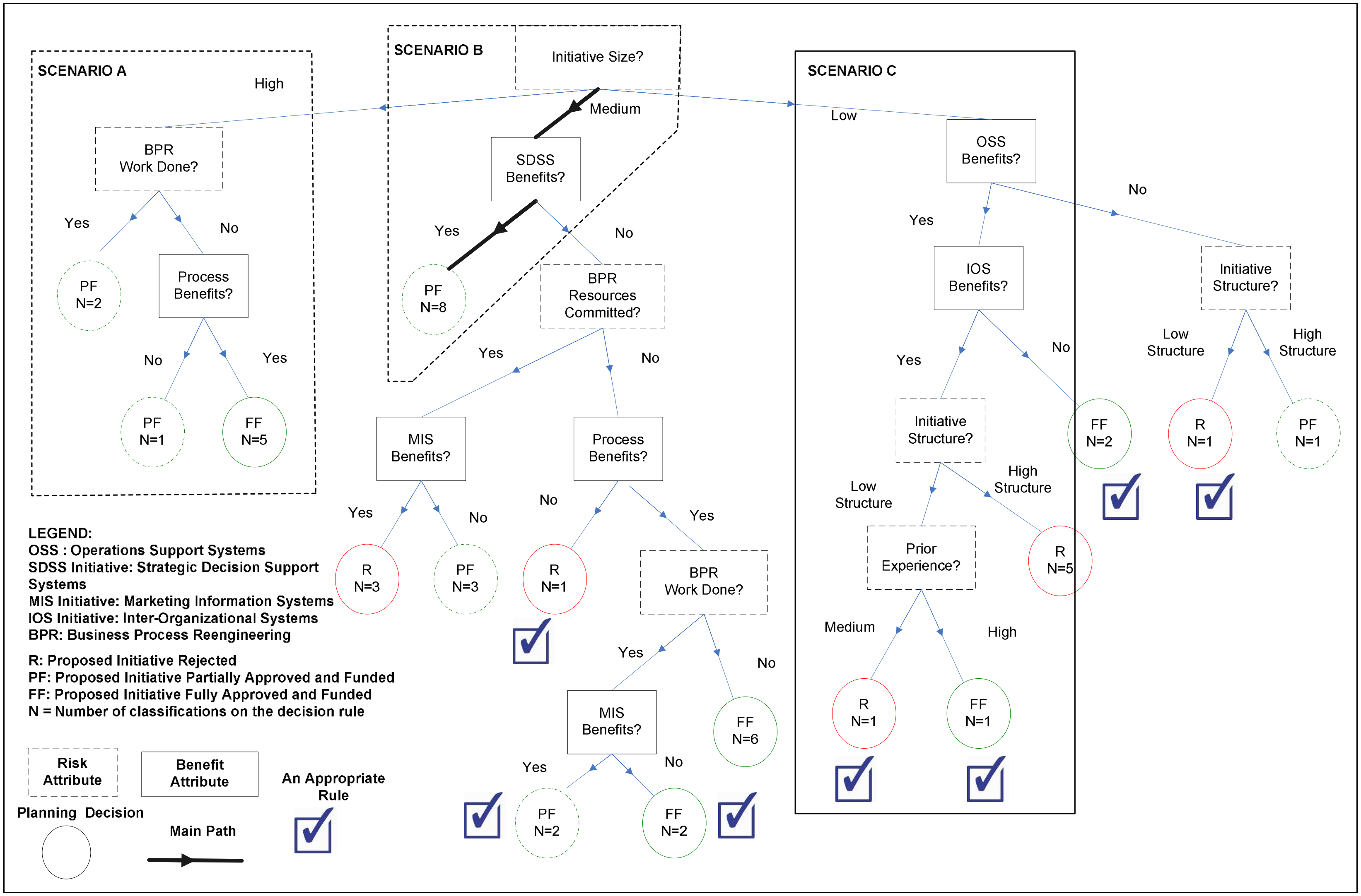

Figure 2. Decision Model (Year One)

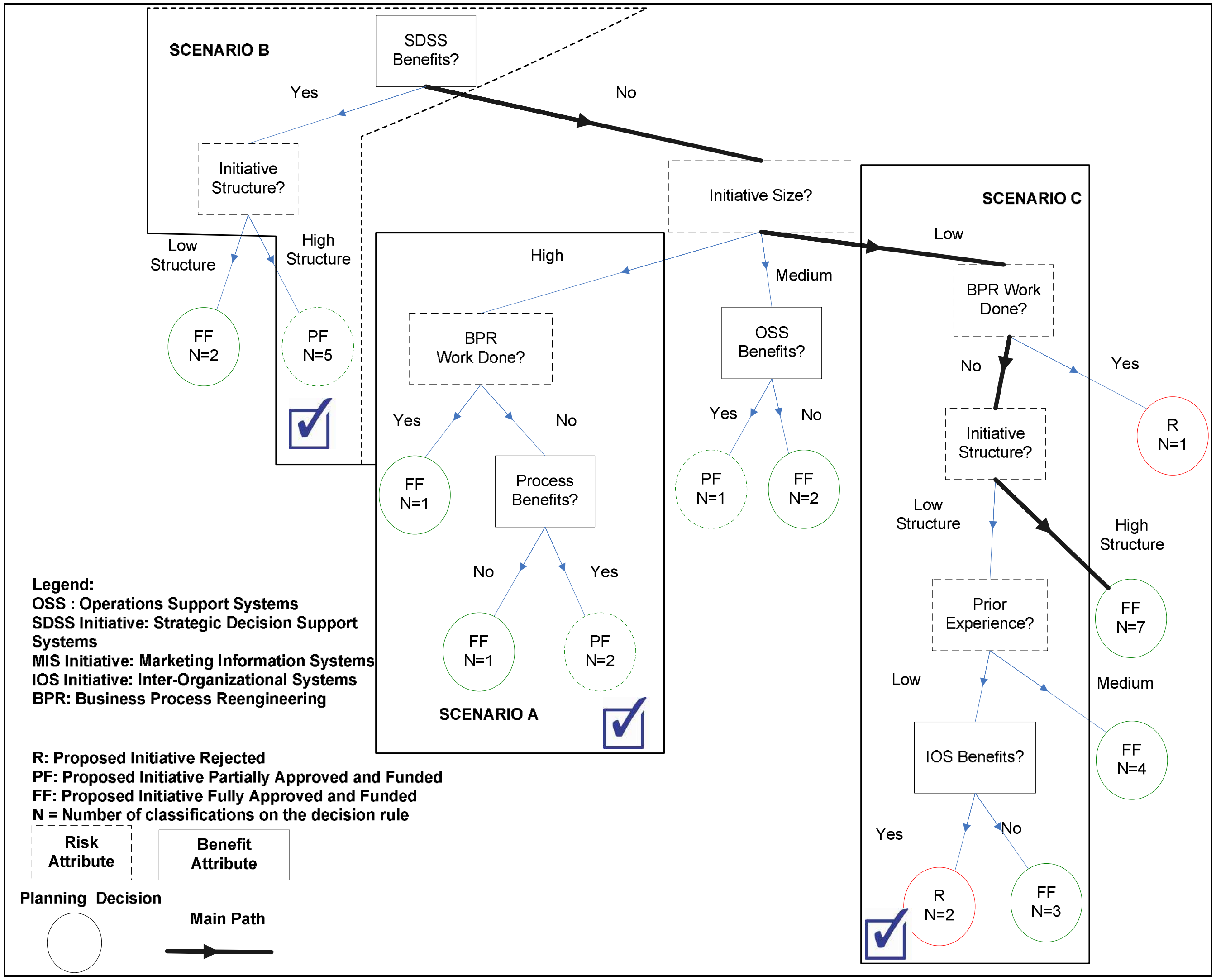

Figure 3. Decision Model (Year Two)

Comparative Findings

A comparative analysis of the two consecutive decision models presented above reveals the following interesting insights. Organizational learning and systematic improvements in the maturity of the planning process are shown by scenarios where decision rules that were inappropriate in the past were refined to design appropriate rules. We elaborate on three instances demonstrating organizational learning. In two instances (Scenario A and B: Table 2), rules which were inappropriate in the past are redefined to design appropriate rules. Scenario C summarizes a refinement to an appropriate rule which was retained in the appropriate form for the future.

	Inappropriate Rule (Year One)	Refined Appropriate Rule (Year Two)
Scenario A	(High Initiative Size) & (BPR Work Not Done) & (Process Benefits) →Fully Approve and Fund Strength of the Pattern: 5	(High Initiative Size) & (BPR Work Not Done) & (Process Benefits) →Partially Approve and Fund Strength of the Pattern: 2
Scenario B	(Medium Initiative Size) & (SDSS Benefits) →Partially Approve & Fund Strength of the Pattern: 8	(SDSS Benefits) & (High Structure) →Partially Approve & Fund Strength of the Pattern: 5

Table 2. Refining Inappropriate Rules

Scenario A: In the first year, 5 high risk initiatives (investments greater than one million dollars) were fully funded even when the decision rule did not show evidence of the presence of any risk mitigation mechanism. The rule suggests that such initiatives were designed to provide process improvements, but the business process rework for such proposed initiatives was not completed during planning. In the second year we find rules with similar structural properties with one key change. 2 similar high risk initiatives were only partially approved and funded. By awarding only partial approval to these initiatives, these initiatives commenced with a narrower scope and additional funding was provided only after the recommended business process rework was completed. 5 initiatives were decided upon using an inappropriate rule in the past; in the second year, evidence of organizational learning suggests that 2 initiatives are being appropriately decided upon. This rule dealt with multi-million dollar initiatives; thus the substantive significance of this improvement is arguably very high.

Scenario B: In the first year, 8 medium sized investments (investments greater than one hundred thousand dollars but less than one million dollars) proposed to deliver strategic benefits were partially approved and funded. There was no evidence to suggest that this rule included any risk mitigation mechanisms. In the second year, similar initiatives were partially approved only after ascertaining that such initiatives were developed with a high structure (higher structure of the proposed initiatives reduces the risks associated with scope creep (McFarlan 1981)). 8 initiatives were decided upon in year one using an inappropriate rule and now 5 similar initiatives were decided upon using an appropriate decision rule. This rule dealt with relative relatively large strategic initiatives; thus the substantive significance of this improvement is arguably very high.

Scenario C: This scenario summarizes a pattern where an appropriate decision rule was retained in the future decision rule set with some refinements. The length of the decision rule is being modified and some of the questions associated with the decision-making (in this context an appropriate rejection rule) are being refined. Consistency in the decision-making is desirable especially for appropriate decision rules.

CONCLUDING COMMENTS

We define the appropriateness of decision rules (with regards to the risk-taking criterion); an important characteristic of rules used during IT portfolio planning. We propose that rule appropriateness will be a key explanatory factor guiding the evolution of rules over time. We use an inductive learning methodology to uncover tacit decision rules used during actual IT portfolio planning over two years within one organization. We present comparative findings which demonstrate systematic improvements in planning rules used over time. In 2 of these 3 scenarios presented, we find that rules that were inappropriate in the first year are being refined to develop appropriate rules for the second year's planning session. We provide empirical evidence to demonstrate organizational learning and highlight the role of rule appropriateness in explaining the evolution of rules used in planning over time. Such continual improvements to the planning capabilities are crucial when planning for IT portfolios. Given that the data used in this study were obtained from one organization, we realize that our findings could suffer from limited generalizeability. In this one instance, we demonstrate the role of rule appropriateness in guiding the evolution of decision rules over time. Though the exact operationalization of rule appropriateness in different organizations is likely to different, we expect rule appropriateness to be a critical guiding force which can guide executives to improve their planning decision over time. Alignment of IT investments has been studied in organizations in the manufacturing industry, and given that we choose an organization in this industry, that can help us improve the generalizeability of our work. Also this organization we examine was classified as an Analyzer; our findings can generalize to other organizations that can be classified as Analyzers. Moving forward comprehensive models explaining the evolution of decision rules over time will be developed based on a comprehensive set of rule characteristics (namely rule length, strength, performance and the causal ambiguity in the application of the rules).

REFERENCES

1. Boynton, A.C., and Zmud, R.W. (1987) Information Technology Planning in the 1990's: Directions for Practice and Research, *MIS Quarterly,* 11, 1, 59-71.
2. Broadbent, M., Weill, P., Clair, D.S., and Kearney, A.T. (1999) Implications of Information Technology Infrastructure for Business Process Redesign, *MIS Quarterly,* 23, 2, 159-182.
3. Eisenhardt, K.M. (1985) Control: Organizational and Economic Approaches, *Management Science,* 31, 2, 134-149.
4. Gentry, J.A., Shaw, M. J., Tessmer, A. C., Whitford, D. T. (2002) Using Inductive Learning to Predict Bankruptcy, *Journal of Organizational Computing & Electronic Commerce,* 12, 1, 39-57.
5. Heugens, P., van Riel, C., and van den Bosch, F. (2004) Reputation Management Capabilities as Decision Rules, *Journal of Management Studies,* 41, 8, 1349-1377.
6. Jeffery, M., and Leliveld, I. (2004) Best Practices in IT Portfolio Management, *MIT Sloan Management Review,* 45, 3, 41-49.
7. Lambert, R.A. (1986) Executive effort and selection of risky projects, *RAND Journal of Economics,* 17, 1, 77-88.
8. Lederer, A.L., and Sethi, V. (1988) The Implementation of Strategic Information Systems Planning Methodologies, *MIS Quarterly,* 12, 3, 445-461.
9. Levitt, B. and March, J.G. (1988) Organizational learning, *Annual Review of Sociology,* 14, 319–340.
10. Luce, R. D., & Raiffa, H. (1957) Games and decisions: Introduction and critical survey, New York: Wiley.
11. McAfee, A.(2007) "Mastering the Three Worlds of Information Technology," Harvard Business Review, 85, 2, 141-149.
12. March, J. (1994) A primer on decision-making: How decisions happen. New York, Free Press.
13. March, J.G., and Shapira, Z. (1987) Managerial Perspectives on Risk and Risk Taking, *Management Science,* 33, 11, 1404-1418.
14. March, J. G. and H. A. Simon. (1958) *Organizations*, New York, Blackwell Publishers.
15. Maizlish, B., and Handler, R. (2005) IT Portfolio Management: Unlocking the Business Value of Technology, John Wiley and Sons, Hoboken, New Jersey.
16. McFarlan, F.W. (1981) Portfolio approach to information systems, *Harvard Business Review,* 59, 5, 142-150.
17. Miles, R., and Snow, C. (1978) Organizational Strategy, Structure and Process, McGraw-Hill, New York.
18. Piccoli, G., and Ives, B. (2005) IT-Dependent Strategic Initiatives and Sustained Competitive Advantage: A Review and Synthesis of the Literature, *MIS Quarterly,* 29, 4, 747-776.
19. Quinlan, J.R. (1986) Induction of decision trees, *Machine Learning,* 1, 1, 81-106.
20. Quinlan, J.R. (1990) Decision trees and decision-making, *IEEE Transactions on Systems, Man, and Cybernetics,* 20, 2, 339-346.
21. Sabherwal, R., and Chan, Y.E. (2001) Alignment between Business and IS Strategies: A Study of Prospectors, Analyzers, and Defenders, *Information Systems Research,* 12, 1, 11-33.
22. Shaw, M. J. and Gentry, J.A. (1988) Using an Expert System with Inductive Learning to Evaluate Business Loans. *FM: The Journal of the Financial Management Association,* 17, 3, 45-56.
23. Shaw, M.J., and Gentry, J.A. (1990) Inductive learning for risk classification, *IEEE Expert,* 47-53.

24. Simon, H.A. (1995) A Behavioral Model of Rational Choice, *Quarterly Journal of Economics,* 69, 1, 99-118.
25. Tessmer, A. C., Shaw, M.J. and Gentry, J.A. (1993) Inductive Learning for International Financial Analysis: A Layered Approach, *Journal of Management Information Systems,* 9, 4, 17-37.
26. Tsoukas, H. (1996) Firm as a Distributed Knowledge System: A Constructionist Approach, *Strategic Management Journal,* 17, 11-25.

APPENDIX 1: SELECTING THE BEST REPRESENTATIVE DECISION MODEL

As can be seen in Table 3, though decision models that had "BPR Work Done" as the top classification attributes were induced most number of times, the error rates for these decision models were consistently high. Decision trees with "Initiative Size" as the top classification attribute, on the other hand, were relatively stable and their error rates were also consistently low. Tree 11 (marked in bold in Table 3) was chosen as the best representative model given its high stability, lowest error rates. A similar methodological approach was used to select the best representative model for year two.

#	L	W	Level Two Attributes	Top Classification Attribute:	Error Rate in Prediction
PANEL 1: (Training set = 70% of original portfolio ‖ Testing set = 30% of original portfolio)					
1	5	15	MIS Initiative, BPR Resources Committed	IOS Initiative	87.5
2	7	16	Initiative size, OSS Initiative	BPR Work Done	50
3	8	21	Initiative size, OSS Initiative	BPR Work Done	43.75
4	9	23	BPR Work Done	OSS Initiative	50
5	7	18	Initiative size, SDSS Initiative	BPR Work Done	43.75
6	6	18	MIS Initiative, BPR Resources Committed	SDSS Initiative	31.25
7	7	18	BPR Resources Committed	BPR Work Done	37.5
8	6	17	BPR Work Done, SDSS Initiative, BPR Resources Committed	Initiative Size	30
9	7	20	BPR Work Done, SDSS Initiative, BPR Resources Committed	Initiative Size	27.5
10	6	17	Initiative Size, BPR Resources Committed	BPR Work Done	50
PANEL 2: (Training set = 80% of original portfolio ‖ Testing set = 20% of original portfolio)					
11	6	16	BPR Work Done, SDSS Initiative, OSS Initiative	Initiative size	18.18
12	6	17	Initiative size, BPR Resources Committed	BPR Work Done	45.45
13	6	17	MIS Initiative, BPR Resources Committed	SDSS Initiative	54.55
14	8	21	Initiative size	BPR Work Done	63.64
15	8	21	Initiative size, BPR Resources Committed	BPR Work Done	54.55
16	8	20	MIS Initiative, OSS Initiative	BPR Work Done	63.64
17	8	20	MIS Initiative, BPR Resources Committed	BPR Work Done	54.55
18	8	16	BPR Resources Committed	BPR Work Done	45.45
19	7	18	Initiative Size	BPR Work Done	45.45
20	8	21	SDSS Initiative, BPR Resources Committed	MIS Initiative	63.64

L = Length of the induced tree, W = Width of the induced tree

Table 3: Improving Reliability of Decision Models with Sensitivity Analysis